# Simulating expected On-Time, In-Full delivery performance for fertiliser transhipment facilities.

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# Management Summary


This study estimates the future On-Time, In-Full (OTIF) performance of 2023 for fertiliser wholesaler Triferto. Additionally, this study experiments with multiple optimisation implementations to meet the OTIF target of 97.5%. Historical data analysis and simulation modelling give an indication of the current performance, and results show that Triferto is on the path of not meeting the target, resulting in receiving financial penalties as written in the contractual agreement with Agrifirm.

**Research goal and context**
Triferto, a customer of CAPE Groep, is an international wholesaler in the fertiliser sector and is the problem owner of this research. Triferto has multiple facilities within the Netherlands that handle different types of fertiliser: bagged and bulk. Triferto's operations include buying, storing, processing, packaging and distributing via contractors. Recently, Triferto entered into cooperation with Agrifirm in which Triferto will be responsible for the supply chain of Agrifirm's fertiliser branches, except sales. This causes a shift in Triferto's operations, resulting in the closing and opening of new and existing facilities, new demand that effectively doubles the yearly tonnages and new requirements to multiple facets set by Agrifirm. One of these new requirements is the delivery performance metric On-Time, In-Full (OTIF). The OTIF target for all yearly Agrifirm orders is 97.5% and Triferto will be financially penalised when the target is not met. Triferto indicates that it is uncertain of meeting this new requirement considering the new situation and states that the culprit of insufficient On-Time performance is likely the loading process. This is defined as the core problem, and leads to the following main research question:

*How can Triferto effectively enhance its future OTIF performance by evaluating current and expected performance, and optimizing loading process capacity management to reach the target of 97.5%?*

**Current performance and Modelling**
Triferto did not measure or monitor OTIF prior to the collaboration with Agrifirm. Therefore, Triferto has no quantitative information on how it would have or will perform regarding the new measure. This research makes a distinct split between the On-Time and In-Full performance of orders due to them being two separate topics that both have different requirements and methods of assessing them.

*On-Time.* Not monitoring prior On-Time performance combined with the challenges of the new situation requires a model to estimate the future performance of in-scope facilities. Discrete event simulation is the model type used. Inputs per facility for this model are demand data, number of loading spots and seasonal capacity characteristics. Due to unavailable quantitative process data of the logistical process, we made substantial simplifications and assumptions regarding forecasts and process details. We use literature and expert information for the expansion and verification of the model. The main tunable parameters in the model are order loading speed, the number of loading spots, and demand characteristics. To further increase the quality of the model and its connection to reality, we study the effects of stochasticity on the system. These are normally distributed loading speeds and a Weibull distribution representing secondary activities like check-in and truck weighing. Additionally, the effects of two optimisations to increase the OTIF performance, adaptive capacity management and the introduction of timeslots, are also studied in the simulation model. Adaptive capacity is used when capacity reaches a utilisation threshold. Then, for the next day, the capacity is increased by the capacity increase factor. The capacity is returned to normal when the return utilisation threshold is reached. Timeslots allow a portion of daily orders to arrive at a certain time, which is set to the beginning of the day for this research due to it being the most efficient.

*In-Full.* Bagged orders are always delivered In-Full, due to them being numerable. Bulk orders have a 200 kilograms error margin in both directions. Historical order data analysis shows that 16% of all bulk orders handled in 2021 exceed this margin. This translates to 11% of all orders in 2021 not being delivered In-Full and sets an upper bound of 89% for the future OTIF measure compared with the target of 97.5%. Facility-wise, Breda performs worst with only 51% of bulk orders In-Full. Heereveen performs best with 95% In-Full, which is still lower than the target.

**Results and Conclusions**

Running the simulation model with the setting Triferto deems the most realistic for 2023 results in the baseline performance for each facility. Combining the results of the In-Full data analysis and the results of the simulation model, we conclude that the expected OTIF score is 91.1%, which implies that Triferto is not meeting the OTIF target of 97.5% in 2023 resulting in financial penalties. Table 1 shows the expected OTIF performance of 2023 in detail and shows that both product types do not meet the target.

| Metric | Bulk | Bagged | Combined |
|---|---|---|---|
| On-Time% | 99.6% | 93.2% | 95.0% |
| In-Full% | 86.1% | 100.0% | 96.1% |
| **OTIF%** | **85.6%** | **93.2%** | **91.1%** |

Table 1: Expected OTIF performance Triferto 2023

To find a setting where each facility meets the OTIF target, we introduce the capacity factor. Multiplying the capacity factor with the loading speed of a loading spot enables capacity variation. Table 2 shows the baseline scenario On-Time performance and the required capacity factor for each facility and product category to meet the 97.5% target. 4 out of 6 bagged handling facilities do not meet the target. Oss is performing the worst, which is due to it having 1 bagged loading spot and attaining a large amount of demand.

| Metric | Breda | Doetinchem | Goor | Heerenveen | Veendam | Drachten | Oss |
|---|---|---|---|---|---|---|---|
| Bulk Baseline | **99.2%** | **99.3%** | **99.7%** | **99.6%** | **99.7%** | **99.7%** | **99.9%** |
| Bagged Baseline | **98.6%** | 93.5% | **97.8%** | 96.1% | 95.6% | - | 81.8% |
| Bulk factor to meet target | 0.7 | 0.8 | 0.5 | 0.6 | 0.5 | 0.5 | 0.2 |
| Bagged factor to meet target | 0.9 | 1.4 | 0.9 | 1.2 | 1.2 | - | 2.0 |

Table 2: Summary baseline and capacity factor setting to meet On-Time target

Overall, introducing stochasticity in two different places has minimal effect on the On-Time performance of the system. The stochasticity induced by the Weibull distribution to simulate secondary activities does not cause additional harm to the performance compared with adding a constant processing time similar to the expected value of the distribution. However, the addition of extra processing time for secondary activities itself decreases On-Time performance and requires 17% additional capacity to compensate. Normally distributed process speeds have a small impact on On-Time performance. Using abnormal standard deviations results in significantly impacting the system's performance. Therefore we conclude that stochasticity has minimal implications for the performance of the system.

Brutely increasing total capacity leads to more unutilised capacity while attaining minimal performance gain. Therefore we discuss the results of multiple other methods to manage capacity. Increasing the number of loading spots while keeping total performance the same does lead to increased performance. Going from 1 to 2 loading spots can lead to a 4.6% capacity saving while maintaining 97.5% performance. This also makes the system more resilient since most late orders occur more when demand comes close to or exceeds maximum daily capacity instead of having late orders spread over the year. Having adaptive capacity management is more effective than increasing capacity when performance is low. Applying this when On-Time performance is 82% results in a 6% capacity and 3.4% On-Time performance increase. However, when nearing the OTIF target, the system does not show significant benefit from the optimisation. Including timeslots results in better performance but loses effectiveness quickly. Experiments show that only allocating 5% of customers to timeslots can have a 2% On-Time performance increase when around 88% On-Time performance. Increasing it further shows little result. Around the OTIF target and in the case of Doetinchem, a 5% timeslot allocation makes performance go from 97.3 to 97.7%, which translates to a potential capacity save of 4 to 7%.

**Reccomendations and Contributions** These are the main recommendations to Triferto following from the research results and conclusions. Consider the expected OTIF performance of 2023 as a serious warning for not meeting the target of 97.5%. Improve data collection, validate the results with experts, and use the try-out year with Agrifirm to proactively identify risks that jeopardise a successful collaboration. Considering underwhelming results when nearing target performance, together with operational disadvantages, we recommend not pursuing the concept of adaptive capacity management. We recommend including the results of this research regarding the use of timeslots in the existing business case and considering a partnership with your main transport partners to start introducing timeslots.

This research contributes to practice by (i) reducing uncertainty around future OTIF performance by showing quantitative results that highlight the risk of not meeting the OTIF target, (ii) studying multiple optimisation implementations supported by literature on their impact on expected delivery performance, and (iii) documenting and combining new qualitative information from experts and additional insights. Unique aspects of the research that contribute to theory compared to similar studies that consider logistical/transport systems with bulk materials are (i) considering a smaller magnitude of the facility, (ii) introducing varying loading/order sizes, (iii) introducing heavy seasonally and assessing performance over a whole year and (iv) being delivery performance focussed instead of having a more economic/efficient focus. Lastly, this study adds to the many studies that deem computer simulation a fit modelling technique to model transport/logistical systems.

# Preface

Na jaren gestudeerd te hebben is het dan eindelijk zo ver om de laatste stap te zetten; het afstuderen voor mijn master Industrial Engineering and Management doormiddel van dit boekwerk. In de afgelopen jaren heb ik veel mogen leren over verschillende vakgebieden maar ook over mijzelf. Daarnaast ben ik oneindig dankbaar voor de mensen die ik de afgelopen jaren heb mogen leren kennen. Een paar hiervan zou ik graag specifiek willen bedanken.

Te beginnen met Triferto en Cape GROEP die mij de kans hebben gegeven om samen een project op te pakken. Ik zou Waria willen bedankt voor de vele malen dat wij naar Doetinchem zijn gereden, de spontane spar momenten, en voor de lekker eet-ideeën die je deelde op de weg terug. Vervolgens wil ik Tijmen bedanken voor het bewaken van de relatie met Triferto, het zijn van mijn bedrijfsbeoordelaar, en het mij betrekken in team Groei waar ik veel heb geleerd, leuke mensen heb ontmoet en lol heb gehad. Ook zou ik graag Jelle en Conrad willen bedanken voor de inhoudelijke bijdrage en het vertrouwen, zonder jullie had er niets in dit verslag gestaan.

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Niet te vergeten, graag wil ik mijn vrienden en familie bedanken voor de ondersteuning tijdens niet alleen het afstuderen, maar ook het studeren zelf. Het zal niet altijd even makkelijk zijn geweest. Martijn wil ik nog even specifiek bedanken voor de extra stimulatie die ik op momenten, ongevraagd, nodig had. Als allerlaatst wil ik Natascha bedanken voor je betrokken- en zorgzaamheid, en je dikke knuffels. Je bent de beste.

Nu is er genoeg bedankt, en is het tijd om de afsluiting van mijn studententijd te vieren met vrienden en familie!

Veel leesplezier,

Sven Koning ter Heege

Enschede, augustus 2023

# Contents

# Chapter 1

# Introduction

This study is conducted in collaboration with CAPE Groep and Triferto and assesses the On-Time, In-Full delivery performance of facilities, which is a new measure for Triferto to assess delivery performance. Section 1.1 explains the companies involved in this research. Section 1.2 explains the motivation behind this research. Next, Section 1.3 introduces the problem and presents two problem statements. Section 1.4 explains the research goals, and Section 1.5 states the research questions that outline this thesis. Lastly, Section 1.6 discusses the scope of this research.

## 1.1 Relevant stakeholders

Three stakeholders are relevant to this research. CAPE Groep is the main stakeholder that commissioned this research. The main problem owner of this research is Triferto, who is a fertiliser wholesaler and a customer of CAPE Groep. The main problem of this research originates from Triferto and Agrifirm entering cooperation. This section introduces them and explains their relation with each other and this thesis.

### 1.1.1 CAPE Groep

CAPE Groep is a consultancy company and has its headquarters in Enschede, The Netherlands. CAPE Groep advises digital transformation to other companies within different sectors like supply chain, agrifood, construction, and logistics. Their focus lies within digital infrastructure, development and integration platforms, web-based software, dashboards, and reporting (CAPE Groep, 2022).

CAPE Groep works together with Triferto on different (digital) projects. CAPE Groep is involved in the development of the webshop where customers can order products from Triferto. CAPE Groep also develops the Backoffice portal where orders are managed, digital connections between transport companies are made, and more. CAPE Groep executes this research and intends to support Triferto in its transformation by using the results of this research.

### 1.1.2 Triferto

Triferto is an international wholesaler in the fertiliser sector and has various storage and transhipment facilities in North-West Europe. The headquarters is in Doetinchem, The Netherlands. Each facility has its specifications, like the ability to manage certain product groups more efficiently than other facilities can or the ability to conduct specific production processes like blending, coating, and bagging. Triferto handles two distinct product types: Bulk fertiliser and Bagged fertiliser. Triferto's operations include buying, storing, processing, packaging and distributing fertiliser via contractors. The shipping process is a big part of Triferto's supply chain and part of its core business, as depicted in Figure 1.1. Many customers choose to make use of this shipping service instead of picking up their product. Triferto also has a webshop where customers can order products, including this transport service (Triferto, 2022). Triferto is a wholesaler in the fertiliser industry and therefore experiences a heavy seasonal peak in turnover during the spring when farmers start working their fields. Triferto is the company

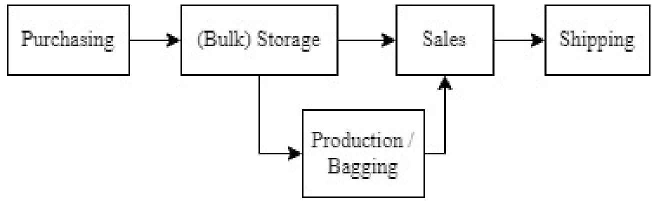



Figure 1.1: Core activities Triferto

where the problem of this research originates. This makes them the problem owner. Therefore, Triferto is the primary source of information and data for this thesis.

### 1.1.3 Agrifirm and collaboration with Triferto

Agrifirm is a Dutch cooperative enterprise that focuses on livestock farming and agriculture. They support farmers in diverse stages of many different types of farmers' supply chains by, for example, selling quality animal feed, crop seeds, fertilisers and crop protection products. Agrifirm was founded in 1982 and has its headquarters located in Apeldoorn, The Netherlands. Currently, Agrifirm has more than 10,000 associates, most of them farmers (Agrifirm, 2022).

Agrifirm wants to outsource its logistical process in the fertiliser branch. This is due to it being one of the smaller branches they operate in compared to their other branches, like animal feed. Buying, storing and shipping fertiliser demands a lot of resources, like space in the form of facilities and tactical purchasing due to it being a seasonal product. However, Agrifirm still wants to provide its members within the cooperative with the option of a complete farming package, which includes selling fertiliser to members who desire it.

Agrifirm and Triferto agreed to enter into cooperation in which Triferto will be responsible for the whole fertiliser supply chain of Agrifirm, except sales. Triferto can presumably do this more efficiently than Agrifirm since it is their core business. The processes Triferto takes over include storage, order handling, bagging, blending and transportation to the customer. Agrifirm provides a demand forecast on a yearly level that is combined with the forecast of Triferto to combine purchasing activities. Inventories for Agrifirm and Triferto customers are digitally kept separate to prevent interference between one's customers. On the operational level, Agrifirm will provide orders that Triferto will fulfil. The main challenge for Triferto is to manage the newly acquired demand, which effectively doubles the yearly tonnages handled by Triferto. Also, there are new and higher requirements for different aspects of the logistical process Triferto will now handle. One of these new requirements is the contractual agreement of a new delivery performance measure by Agrifirm of the orders that Triferto manages. This will be measured using the On-Time, In-Full (OTIF) measure. There are financial consequences for Triferto if it does not meet the OTIF target of a 97.5% success rate for all orders. Triferto also states that it is highly uncertain of its capability to reach the target and cannot establish its current OTIF performance.

## 1.2 Research motivation

This section gives the motivation for this research conducted at Triferto with CAPE Groep. Section 1.2.1 defines the new delivery performance measure OTIF whereas Section 1.2.2 explains the OTIF target and why it is the main motivation for this research.

### 1.2.1 On-Time, In-Full Performance Measure Definition

The cooperation between Triferto and Agrifirm positions Triferto within the supply chain of Agrifirm. Agrifirm wants to offer its customers a certain level of service. Delivering orders OTIF is part of the contractual agreement between Triferto and Agrifirm. According to literature, performance indicators that contribute to supply chain resilience are order and delivery lead time, on-time delivery, supplier delivery efficiency and customer satisfaction (Leitea et al., 2018). OTIF is frequently encountered as a measure of the perfect order (Christopher, 2016). As the name implies, one of the targets considers the moment of delivery, and the other focuses on the accuracy of the delivered amount. These two targets are binary. A successful order completion means that the order is delivered both On-Time and In-Full. Equation 1.1 shows how the OTIF score is calculated. An order does not contribute to the OTIF score when at least one of the two performance measures is not met.

$$OTIF\ score = \frac{Number\ Of\ Orders\ OTIF}{Total\ Number\ Of\ Orders} \tag{1.1}$$

In the case of Triferto and Agrifirm, a successful order that contributes to the OTIF score is defined as follows; (i) the order is delivered on the target date (On-Time) and (ii) the order is delivered and matches the ordered amount, within a pre-specified margin of error.

### 1.2.2 Contractual OTIF Target of Agrifirm orders

By contractual agreement, the OTIF target is set to 97.5% of all Agrifirm orders that are handled by Triferto. Triferto incurs a significant financial penalty when they do not meet this yearly target. However, when the OTIF score exceeds 98%, Triferto will receive a financial bonus. The first year (the season of 2023) will be a try-out. This means that there will be no financial penalties for Triferto for not meeting the OTIF success target of 97.5%. This try-out year is to see if the requirements set within the agreement are deemed realistic, give Agrifirm and Triferto a chance to revisit their agreement and give Triferto time to learn from their first year and make adjustments to their processes accordingly.

It is uncertain if Triferto can meet the OTIF target set within the agreement. The OTIF score is a new delivery performance measure for Triferto and was not measured in previous years. These targets and their properties are discussed with experts within the organisation, such as facility managers and planners. They were deemed achievable, considering the first try-out year. Also, Triferto's limited data collection gave little to no insight into what to expect considering the On-Time and In-Full performance of orders. Therefore Triferto did not quantify the likelihood of reaching these OTIF targets and based their feasibility on the opinion of experts. Triferto has confirmed these uncertainties and says additional research into the future OTIF performance is urgent to meet Agrifirm's and their expectations regarding delivery performance and guarantee customer satisfaction. It is expected by Triferto that there is a substantial risk of not meeting OTIF delivery standards, especially when the fertiliser season is in full swing if no measures are taken.

The main research motivation for the future OTIF performance of delivering Agrifirm orders by Triferto is the apparent uncertainty of meeting the set targets of the agreement, mainly considering the On-Time delivery. This uncertainty leads to a risk of financial penalty. Secondary motivators are improved customer satisfaction when monitoring/improving delivery performance, increased insights into processes due to the start of new data collection and potential other insights that arise when researching the topic of OTIF delivery performance.

## 1.3 Problem Definition & Statements

The collaboration between Agrifirm and Triferto will be a challenge, especially for Triferto. This research is specifically about the new OTIF delivery performance measure. The OTIF measure has two individual aspects that each have their own problems, which the following two subsections address.

### 1.3.1 On-Time - Loading process

There are multiple causes identified within Triferto that cause late delivery (not On-Time) of orders that are shown in the following list.

- **Available Stock** - Not enough available raw materials or final product in stock to fulfil demand in time.
- **Production Capacity** - Insufficient production capacity to blend or bag fertiliser into the final product in time.

- **Loading process** - Not able to fulfil daily orders due to insufficient throughput capacity within the loading process resulting in delayed delivery of orders.

Supply chain employees and facility managers indicate that orders that cannot always be delivered on the requested day due to insufficient throughput capacity within the loading process are one of the more common causes of late deliveries. For this research, we focus on the main cause of late delivery. Section 1.6 explains this scoping and its implications in more detail. The throughput capacity of the loading process at a facility is the total amount of product that can be loaded into trucks at one facility in a period, given that the final product is in stock. This throughput capacity is expressed in tonnages per time unit for each product group (Bulk and Bagged) and can differ with each facility. There is no quantitative process performance data to determine this throughput capacity since Triferto does not monitor internal processes. However, Triferto specifies the throughput capacity as the loading speed of a loading spot in tonnages per week times the number of available loading spots per product category. The formula 1.2 explains the maximum throughput capacity and is based on general historical data and expert opinions. A loading spot is a space within a facility that is reserved for loading trucks. These are restricted to one of the two product types.

The available capacity varies during the year as a percentage of this maximum capacity, which reflects seasonal demand. These periods are defined by Triferto. Different indicators are considered during the order allocation process, like available inventory, but the expected load caused by demand on the facilities' loading process and its throughput capacity are not. Also, the throughput capacity of the loading process has a direct link between orders that cannot be fulfilled in one day and the On-Time aspect of the OTIF delivery performance of those orders. The exact link between the factors that determine the throughput capacity in the loading process and On-Time performance is unknown. Analysing and simulating the loading process can give additional insights regarding capacity management, resource utilization, and delivery performance throughout the year in different scenarios. The problem statement related to the On-Time delivery performance of this research is as follows:

*"Triferto is uncertain about meeting daily demand and reaching the set OTIF target of 97.5%, due to the unknown impact of the throughput capacity of the loading process, and the factors determining it, on its On-Time delivery performance for each facility."*

$$\textit{Max. throughput capacity of loading process} = \textit{Loading speed of single loading spot} * \textit{Nr of loading spots} \tag{1.2}$$

### 1.3.2 In-Full - Order Loading Inaccuracy

The difference between the actual delivered amount and the ordered amount is unknown. Triferto does not monitor the ordered amount and only saves order data which contains the delivered amount, overwriting the ordered amount. This becomes a problem because Agrifirm requires orders to be delivered In-Full, by allowing an error margin of 200 kilograms for bulk orders and no error margin for countable bagged orders. Triferto needs to start measuring its In-Full performance and report this to Agrifirm, and manage it so that at least the OTIF target of 97.5% is reached. However, this still leaves Triferto with the uncertainty of their expected In-Full delivery performance. This creates the following problem statement regarding the In-Full delivery performance of this research:

*"Triferto is uncertain whether their current In-Full delivery performance is sufficient to meet the set OTIF target of 97.5%, due to the reliance on qualitative expert opinions and the absence of prior internal measurement."*

## 1.4 Main Research Question & Objectives

To tackle the two problem statements related to the uncertainty of future OTIF performance presented in Section 1.3, we formulate the following main research question of this thesis:

*How can Triferto effectively enhance its future OTIF performance by evaluating current and expected performance, and optimizing loading process capacity management to reach the target of 97.5%?*

To properly answer the main research question and to give solid insight and recommendations to Triferto within the context of the new situation originating from the collaboration with Agrifirm regarding OTIF delivery performance, we set the following three objectives of this research:

1. **Study current In-Full delivery performance to identify gaps to target OTIF score.** Determining the currently unknown In-Full delivery performance of all orders at different facilities decreases the uncertainty in current performance and gives Triferto insight into the gap to reach the OTIF score target. This study analyses historical order data to extract previously unmonitored insights into the historical In-Full delivery performance. The result of this study decreases uncertainties of Triferto's In-Full performance, shows if this performance is sufficient to meet the OTIF target and explains performance differences amongst facilities to potentially find a flagship facility to take best practices from to further improve existing and opening facilities' loading accuracies.

2. **Find factors and their relations to further increase understanding of the impact of throughput capacity on the On-Time performance of Triferto's facilities.** Key to understanding the concept of throughput capacity of the loading process within the context of Triferto is to further study the context and what factors have an impact on the capacity. This study consults both various data sets & employees within Triferto and available literature that describes related problems. This gives Triferto a better understanding of the factors that determine the throughput capacity and the impact on delivery performance, which enables them to better manage it and sets up a basis for the next research objective.

3. **Combine said factors to model the loading process at Triferto's facilities to assess future On-Time delivery performance regarding the new Agrifirm collaboration.** Modelling the loading process for Triferto's existing and opening facilities enables the testing of different scenarios, which is designed to reflect the new situation of Triferto collaborating with Agrifirm. Experimenting with the factors determining throughput capacities, like available loading spots and loading spot capacity, leads to finding the future On-Time performance of the loading process in the new demand pattern. We require a computer model to reach this objective. Simulation modelling is the chosen method for this research. Triferto indicated that many different factors may have an impact, small or big, on the throughput capacity of a facility. Simulation enables us to experiment with these parameters without the need to make expensive investments in the real system (Seila, 1995). The results of experimenting with this simulation model yield an increased understanding of future On-Time performance in different scenarios and settings that are relevant within the problem context. These scenarios and settings include varying demand, factors determining available capacity and optimisation features. Secondary insights that are of value to improve business processes are also documented.

These three objectives together reduce Triferto's uncertainty in immediate future OTIF performance within the context of the collaboration with Agrifirm, map the current situation that contributes to managing and/or improving processes that affect future OTIF performance, and give an expected future performance in scenario's that identify risks & opportunities to meeting the OTIF score target of at least 97.5%.

## 1.5 Research Questions & Thesis Outline

This section defines five questions that help answer the main research question and reach the goals of this thesis that Section 1.4 formulates. These questions give an outline for the rest of this thesis and are connected to a specific chapter. The section with each research question gives a brief explanation of the goal of that particular chapter. Figure 1.2 gives a visual overview of the structure and contents of this thesis.

**Chapter 2: Current Situation Context Analysis**

RQ1. *Can Triferto determine the historical OTIF delivery performance, and if so, what is the performance?*

This first research question focuses on gaining more context of the current situation and its readiness for the new delivery performance measure OTIF. The chapter analyses historical data to find how Triferto would have performed on such a measure and gives more context to the relation between throughput capacity and On-Time performance.

**Chapter 3: Literature review**

RQ2. *What does the literature state about the relation between delivery performance and throughput capacity, the impact of throughput capacity on the On-Time delivery performance, and what methods are used in similar business contexts to manage throughput capacity to increase On-Time delivery performance?*

In answering this research question, Chapter 3 reviews the available literature. First, it is important to study the relationship between delivery performance and the throughput of a system. With this, we gain a better understanding of the link between throughput capacity and On-Time performance, building on Triferto's findings regarding the logistical process. Second, the data about individual processes within the loading process of Triferto's facilities is insufficient to build a valid model. Some of these gaps are filled by studying literature and cases that have similar processes. Lastly, literature is studied to review simulation modelling as the modelling method to address the second problem statement in Section 1.3.2.

**Chapter 4: Model**

RQ3. *How to define a simulation model that abstractly describes the impact of the throughput capacity on the logistical process of Triferto's facilities to estimate On-Time delivery performance look like, and what information, parameters, and assumptions are required to make a valid simulation model?*

This research question focuses on gathering the information required to build a valid simulation model to assess the logistical process and determine the expected On-Time delivery while experimenting with factors impacting the throughput capacity. First, the chapter combines the findings of the context analysis in Chapter 2 and additional findings about logistical processes in Chapter 3 to build a simulation model. This model has multiple outputs that show the performance of individual settings, with the percentage of total orders that are delivered On-Time being the most important output. Lastly, multiple experiments are designed that give a better understanding of the logistical process and how the factors determining throughput capacity impact the On-Time delivery performance and capacity utilisation.

**Chapter 5: Experiments and Results**

RQ4. *What model configuration is required to meet the On-Time target of at least 97.5% while minimising maximum throughput capacity for the different facilities Triferto operates?*

To answer this research question, we execute the experiments designed in Section 4.3 and study its results to find configurations for each facility that meet the On-Time target of at least 97.5% while the maximum throughput capacity. Next, it shows the results of the implementation of the adaptive capacity management method described by Land et al. (1999). Lastly, we test the effects of introducing different types of stochasticity to the system in the form of normalised processing times and adding secondary activities.

**Chapter 6: Conclusions and Recommendations**

RQ5. *What are the main conclusions and recommendations regarding the In-Full performance data analysis and logistical process simulation assessing In-Time performance to increase future OTIF delivery performance?*

In answering this research question, we combine all findings and results into conclusions and recommendations to Triferto regarding their new OTIF delivery performance measure. Combining the historical data analysis of the In-Full delivery, and the results of the simulation study that assesses the On-Time performance, gives a complete picture of the (potential) future OTIF performance, the probability of reaching the target of 97.5% gives the information to answer the main research question and provides the foundation for recommendations to Triferto regarding the two problem statements.

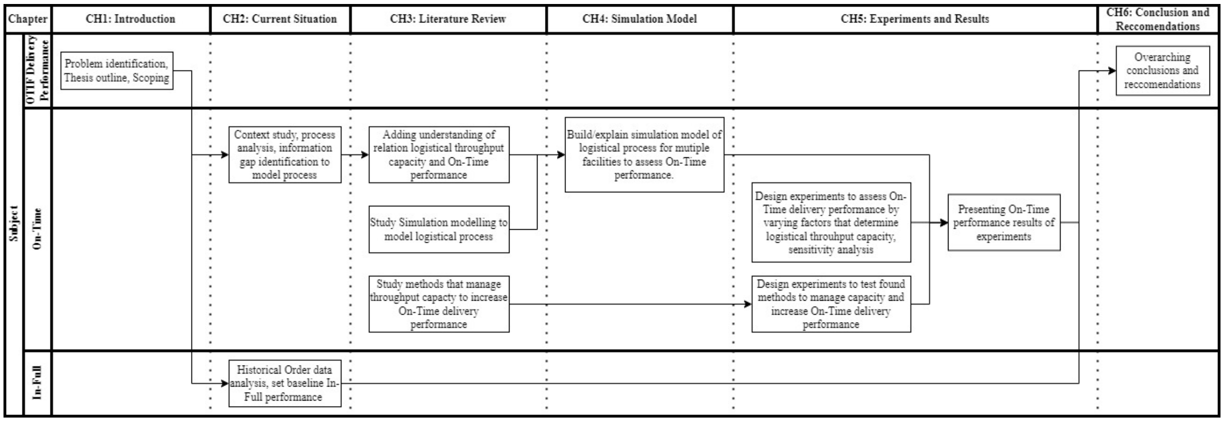



Figure 1.2: Overview of relations between thesis contents

## 1.6 Scoping

This section gives details of certain topics concerning the scope of this research.

**Late delivery core problems.** There are three main causes of late deliveries that Section 1.3.1 lists. All three causes attain the same problem of late deliveries. However, each cause has a different process and problems that cause it to fail, which results in late deliveries. Including all these processes would result in a scope that is too broad. This would require extensive data gathering and time studies at multiple facilities. Also, results would be less impactful regarding delivery performance due to them having less effect on it than the loading process. Therefore we only include the loading process in this thesis, and assume that there is always sufficient available stock and production capacity to fulfil orders in the simulation model. The impact of this scoping is that the final OTIF score reported in the model is only considering the performance of the loading processes. Therefore, the results of this thesis should be interpreted as the expected performance of the loading process and not the true OTIF performance of the whole system. The true performance is likely worse due to the additional impact of the out-scope subjects.

**Facility consideration.** Triferto has multiple facilities besides their headquarters that function as storage and production sites in north-western Europe, of which the majority are located in the Netherlands. Agrifirm serves only customers within the Netherlands, and therefore, we only include facilities located in the Netherlands. The availability of internal information and stakeholders is an additional reason not to assess all facilities. However, the results of this thesis are scalable to facilities outside of the scope. Facility Kampen handles liquid fertiliser, which has an entirely different process than bagged and bulk product types. Therefore, Kampen is out of scope. This research considers the following facilities during the analysis of historical data for 2021; Blauwverlaat, Breda, Doetinchem, Goor, Heerenveen and Veendam. When considering the new situation, this research leaves out Blauwverlaat due to closure and adds Drachten and Oss as new facilities. Drachten and Oss have no available historical data.

**Order types and allocation.** There are diverse types of orders regarding aspects like packaging, customer, truck and delivery type. Each of these order types has its characteristics and contribution to the daily throughput of a facility. Because each order type affects the processes of a facility differently, we will consider all types within this research. Section 2.1.1 explains the order types and their properties in more detail. Currently, a new order is immediately assigned to a location, automatically or by hand, depending on the ordering method, when a customer places it. This is based upon which facility is closest to the customer to minimize transport costs and has enough stock of the ordered product. Thus, there is no single demand allocation moment per day to consider all orders and locations. Therefore, choosing the right facility when the order is placed is important to prevent corrective actions and minimize operational and transport costs due to sub-optimal planning. The research objective is to gain insight into what determines the throughput capacity of the loading process and how a facility reacts to a certain load. Therefore, the allocation and planning of orders is out of scope but an interesting subject for further research where the results of this thesis can be used as input. The impact of this scoping is that actual demand patterns can differ from the demand used in this thesis. This is due to closing old and opening new locations, which likely cause differences in future demand allocations to a facility in comparison with historical allocations. This is mitigated by partly using current season data in combination with forecasts to enhance demand accuracy over the facilities in the simulation model. Also, manual corrections are made to demand data used in the simulation model that reflect the possible shift in demand in consultation with key stakeholders.

## 1.7 Conclusion

This chapter explains the new situation of Triferto and the collaboration with Agrifirm and identifies the main problem related to the new delivery performance measure, OTIF. 97.5% of all Agrifirm orders should be delivered On-Time and In-Full, or else Triferto will be financially penalised. The main problem of Triferto is the uncertainty of their current and future OTIF delivery performance and, thus, the achievability of this new performance measure. Also, Triferto has indicated that it has serious doubts about its capabilities to reach this target. The goal of this research is to reduce this uncertainty by giving Triferto valuable insights about their current and future OTIF performance by historical data analysis and simulation modelling. Both the On-Time and In-Full aspects are separately addressed throughout this research. The next chapter dives into the information required to solve the main problem and identifies the information gaps, which are later addressed in this thesis by historical data analysis, reviewing literature and simulation modelling.

# Chapter 2

# Current Situation

In this chapter, we study the context of the processes that have an impact on both the parts, On-Time and In-Full, of the delivery performance. We study historical order data and consult with experts to set a baseline OTIF performance which is currently unclear. Section 2.1 gives more insight into the organisation, order characteristics & handling and differences amongst facilities. Section 2.2 explains the throughput capacity in more detail, which is based on observations, and interviews with key stakeholders. Next, Section 2.3 describes what OTIF means for Triferto and her organisation, whereas Section 2.4 determines the historical performance of both measures. Section 2.5 concludes the chapter in a point-by-point summary by answering the first research question and explaining what this chapter contributes to the first two research objectives.

## 2.1 Additional context

This section gives additional context that explains the problem more and gathers information to assist in answering the first sub-question. Section 2.1.1 explains the different order types and how Triferto manages them. Section 2.1.2 explains how an order is handled, specifically when the facility manager receives it. This is visualized in Figure 2.2.

### 2.1.1 Order types

Each customer order has two distinct attributes, which together form an order type. The first attribute is the delivery type. This can be pick-up by the customer or delivered to the customer by an external transporting company. The other attribute is the product type. This can be bulk or bagged fertiliser. Bagged fertiliser can be of two distinct types; bagged in big bags of around 1 cubic meter or smaller sacks, which are stacked and sealed on a pallet. Figure 2.1 shows the orders' attributes and what form they can take.

Orders and their attributes determine how they are handled when being loaded on a truck. By consulting facility directors about the impact of different order types on the throughput capacity, we can conclude that bulk products can be loaded relatively fast via a big bucket loader or by positioning the truck under a silo. Orders that have bagged products often require the most effort to load due to forklift loading. Section 2.2 explains this logistical process in more detail. The forecast of Agrifirm shows that the biggest part of their extra demand will come in the form of bagged products, which will mostly be delivered directly from a facility to the customer. Therefore, we expect that the available throughput capacity related to loading these products into trucks will be critical and most interesting for this research for the next season.

### 2.1.2 Order handling

Orders can enter the organisation in three ways. Customers can place orders by contacting the Backoffice via mail or telephone, enter their orders via Triferto's online portal TrifertoWeb or directly contact the facility manager to ask if there is enough product available. When the customer chooses to pick up the product on their own, the order is placed at the facility of choice that has the desired product in stock. When the customer chooses a

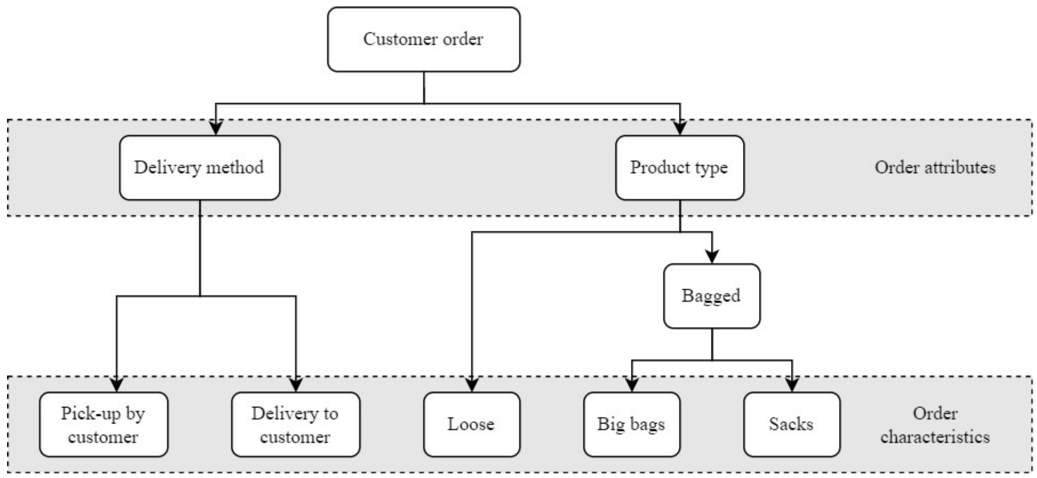



Figure 2.1: Order attributes and characteristics

delivery to the requested location, the order is assigned to the closest facility that has the final product, or its raw materials when production is required, in stock to minimize transport costs.

When judging if a facility has sufficient inventory to accept, Triferto considers the ‘free inventory’ when the order is placed. Free inventory is the remaining inventory after subtracting orders that are placed but are yet to be handled from the actual Triferto or Agrifirm inventory. This depends on whether Agrifirm or Triferto’s customers place an order. This is to prevent a negative inventory, which occurs by accepting orders that Triferto does not have the inventory for. This measure also prevents giving customers a false order confirmation. Note that it is sometimes possible to have a negative inventory, but only when it is given that there are sufficient raw materials available to produce the final product. Delivery lead time when a customer places an order that needs to be delivered as soon as possible varies from 3 to 5 working days. This depends on the product type and level of product customization. This lead time is used so that the facility that handles the order has sufficient time to produce the order when required and make the order ready for pick-up or delivery. No other matters than the free inventory and the shortest distance from the facility to the customer are considered in the order handling process. This means that throughput capacity is not considered, while it is being brought forward as one of the main issues of late deliveries.

When the Backoffice does the initial checks if an order is feasible and assigns it to the facility, and when a customer requests an order at the facility itself, the facility manager handles the order as shown in Figure 2.2. Despite the initial feasibility check by the Backoffice, the facility manager may deem the order as infeasible in its current state. Causes can be inventory data discrepancies or factors that are not considered during allocation, like throughput capacity. When this event occurs, the facility manager cancels the current order and discusses if they can figure out a solution, like delayed delivery or supplying a different product with the Backoffice and/or customer.

### 2.1.3 Facilities

Triferto operates multiple facilities at different strategic geographic locations within the Netherlands. While the core business is the same for all the facilities, there are differences between them. The first main difference is the total amount of product each facility handles. Throughout this thesis, we used normalised data to prevent showing sensitive information, normalised being the percentage of the largest figure used within the series. Figure 2.3 shows with the dashed bar the total normalised tonnages for each facility over 2021. Another difference is the specialization of facilities. The figure shows that some facilities specialise in one specific product type. The layout and available equipment also vary over the facilities, which impacts the loading process and its available throughput capacity. For example, Doetinchem has one central weighing bridge at the entrance, whereas Goor has its bridge under the loading silo. This means that, especially when loading different products in bulk in one

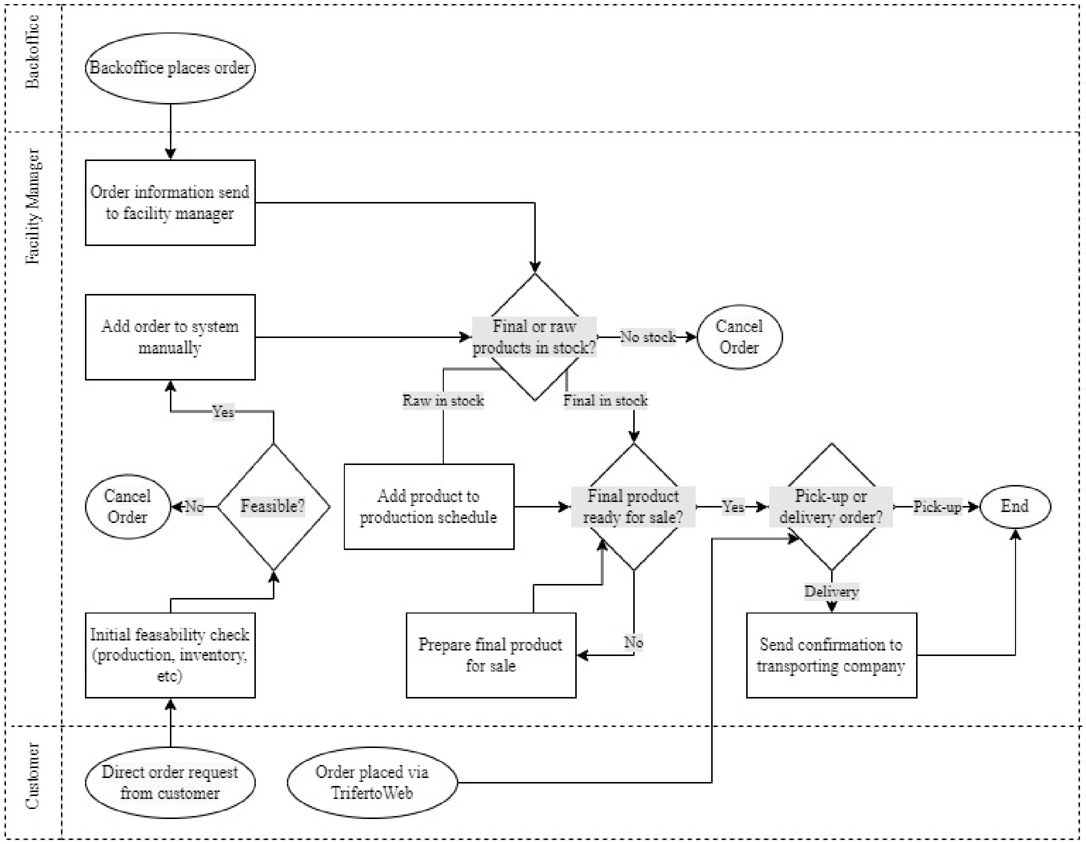



Figure 2.2: Order handling activities by Facility Manager

truck, this process is more efficient in Goor than in Doetinchem. In turn, Doetinchem is far more spacious than Goor. This results in trucks being able to move more freely and convenient loading, especially bagged products. Goor's production facilities to make bagged products are favourable compared to other facilities. Due to storage limitations, Goor rents an extra storage lot some distance away to store bagged products which then can be loaded on trucks destined for customers or other facilities. Much like the difference explained between Goor and Doetinchem, each facility has its specifications and specializations are never the same. Triferto knows that there are differences, but they are not documented or quantified for each location.

The collaboration between Triferto and Agrifirm roughly doubles total demand, new quality standards related to warehousing and new delivery performance targets that Section 1.1.3 explains. Therefore Triferto requires to make significant changes to her collection of facilities in different facets. New canopies are built to meet the new storage quality standards and equipment is acquired to increase the throughput capacity of various facilities. Two new facilities, Drachten and Oss, will be rented from Agrifirm to increase total capacity. Also, the facility in Blauwverlaat will be closed due to high upcoming maintenance costs. Drachten will take over the demand of Blauwverlaat due to it being the closest facility. The change in demand, the new acquisition of facilities, the use of new performance measures and the change in available equipment at facilities make it a challenge for Triferto to manage its resources and meet demand with a certain delivery standard for both itself and Agrifirm.

### 2.1.4 On-site Logistical Process

This section explains the procedures that are initiated when a customer enters a facility to pick up an order. Figure 2.4 shows these processes when a truck arrives at the facility to pick up an order. In the following scenario, we take the facility Doetinchem as an example. The check-in process for a truck arriving takes about five minutes. The waiting time depends on other customers already being loaded, or loading equipment availability of for example

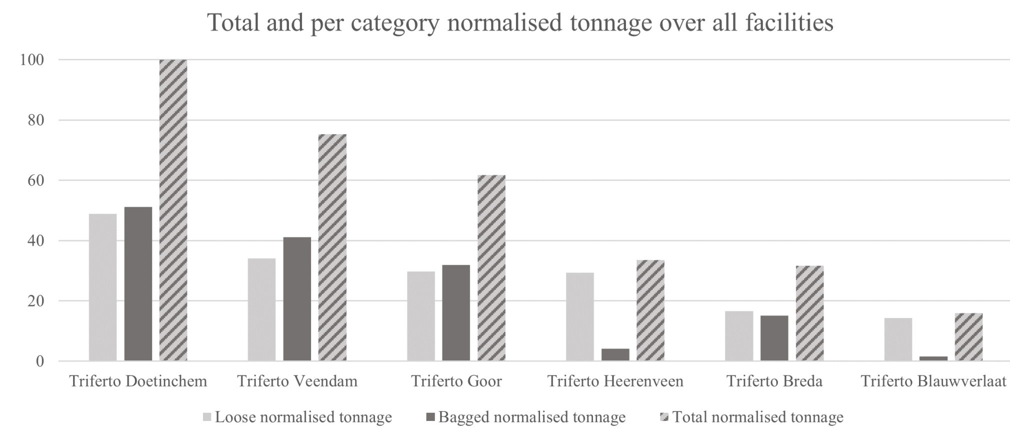



Figure 2.3: Bulk, bagged and total normalised tonnages for each facility Triferto operated in 2021

forklifts. Next, we discuss the loading time of the two product types. The loading speed of bulk products is about nine tonnes per minute with a maximum of about 35 tonnes when loading under a silo, whereas loading a truck with 51 big bags (maximum capacity) takes about 15 to 20 minutes. The next step, for bulk products, is measuring on the weighing bridge how much product was exactly loaded. Lastly, the truck checks out at the facility manager and is on its way.

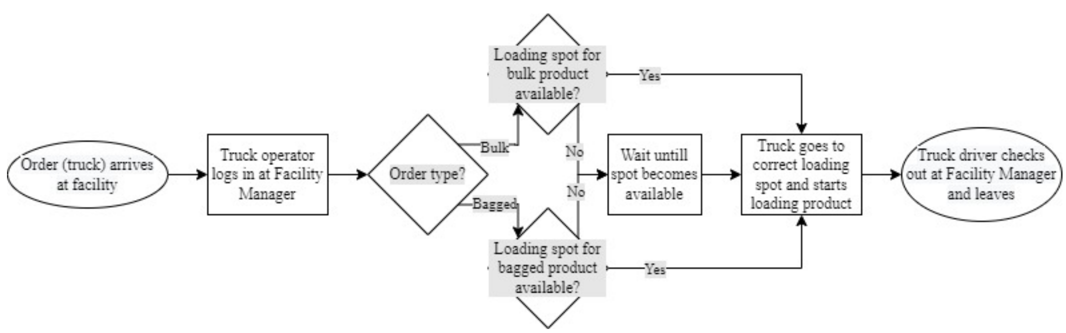



Figure 2.4: On-site logistical process of loading an order

Each facility has its characteristics that determine how efficiently certain order types can be processed and their impact on the available throughput capacity. However, these characteristics are mostly quantitatively described within the organisation, and Triferto lacks the process data/times to support and quantify these characteristics. The next section explains the throughput of this system.

## 2.2 Throughput Capacity of the loading process

This section builds on the definition of the throughput capacity of the loading process set in Section 1.3.1 by addressing the details of it within the organisation and how it is embedded in the logistical process that handles order loading. Section 1.3 mentions some events that jeopardise the On-Time delivery performance of orders for Triferto specifically, while we focus on the impact of the throughput capacity on the On-Time delivery of orders.

Multiple factors determine the throughput capacity. Various employees with different roles have indicated that the factors shown in Table 2.1 have a significant impact on and determine the throughput capacity of the loading process. Next to the item, some context is given on how it has an impact on the throughput capacity. These factors differ per facility and determine process times like single pallet & big bag loading times, set-up times, check-in times, and bulk loading capabilities. These parameters change during the year because full capacity is not required during the entire year due to heavy seasonality. During the season, most resources are used to facilitate logistical throughput, while during the off-season more are used for inventory management, production and filling inventories by e.g. unloading boats to refill inventories for the next season.

| Factor | Relation to throughput capacity |
|---|---|
| Loading spots | The number of loading spots available for each product group determines the number of trucks that can be loaded at the same time, given other required equipment and employees are available. |
| Forklifts | The number of available forklifts influence the loading speed of a truck, specifically for bagged goods. Also, the quality and configuration of the forklift impact its influence. |
| Bulk loading equipment | Size & availability of bucket loaders, transport belt capacity, and silo capacity all have an impact on the direct loading capacity. Also, loading on a weighing bridge is more efficient than a truck being required to drive to a central weighing bridge. |
| Employees | Enough available personnel are key to having sufficient capacity. It is a labour-intensive process and equipment often needs an employee to be operated. This goes together with the necessary skill to operate such machinery. So the skill level is also important to the capacity. |
| Storage location | The storage location, accessibility and distance to a loading spot on the facility especially for bagged products impact the trip time to load a pallet or big bag. |
| Shift times | Shift times determine the amount of time available each day to do logistical operations and load orders. |

Table 2.1: Factors and their relation to throughput capacity according to employees.

Triferto cannot be considered data-driven regarding its throughput capacity and customer satisfaction metrics. The amount of data gathering that gives insight into the factors that determine process times, which in turn determine the throughput capacity, is extremely limited and varies with each facility. Specific information regarding the logistical process such as the throughput capacity of a single loading dock, individual process times and availability of resources that would be considerable inputs for the simulation model are not available or loosely based upon expert opinions. These expert opinions originate mainly from the facility managers and are often simplified. Triferto did not have much reason to implement data collection due to overcapacity during the majority of the year and not managing delivery performance. However, during the yearly seasonal peak, the logistical process of a facility becomes critical and sometimes the workload exceeds the capacity. Because of the collaboration with Agrifirm, the yearly demand for Triferto is doubled tonnage-wise. This increase is managed by limited but smart expansions related to the number of facilities, storage facilities, and increased production capacity, but also investments related to the throughput capacity. Despite these expansions, the prospect is that the loading process amongst the facilities will be critical more often. To gain more insight into this process, we analyse historical order data and interview stakeholders such as the supply chain department, (capacity) planners, facility managers, and employees both in the headquarters and on the facilities themselves.

The available information about throughput capacity of the loading process is limited and specified as the multiplication of the loading speed of a loading spot in tonnages per day, and the number of available loading spots. This is specified separately for bagged and bulk and varies per facility. This capacity 'considers' everything the list above mentions, which makes it essentially a rough estimate. There are no supplementary calculations available that can give details into the underlying factors that determine this capacity. Triferto implements a form of capacity flexibility by reducing maximum capacity during the year which follows the seasonal trend of fertiliser sales. This is not done continuously, but in three levels between 44% and 100% set to certain weeks of the year based on forecasts. This capacity throttle is the same overall facilities but differs slightly per product type. Figure 2.5 shows the variable capacity trend with the expected demand of 2023 to highlight the capacity following the seasonal demand pattern. Note that the line representing capacity is the percentage of the theoretical maximum capacity throughout the year. The actual capacity is unknown. Together with additional literature research about the relation between OTIF and the throughput capacity and factors that influence it in Chapter 3 leads to a basis to model the logistical process in Chapter 4 and assess the On-Time performance of the system in different scenarios with varying throughput capacity.

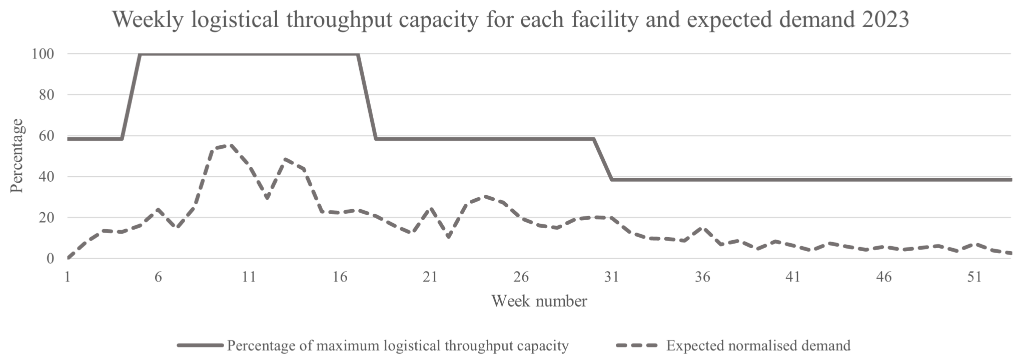



Figure 2.5: Variable throughput capacity in percentages, following seasonal trend

## 2.3 OTIF within context Triferto

This section explains the specifics regarding OTIF delivery within the context of Agrifirm and Triferto by discussing the specific delivery requirements and what they mean for Triferto. Section 2.3.1 explains the On-Time measure in more detail and Section 2.3.2 does the same for the In-Full measure.

### 2.3.1 Context On-Time delivery at Triferto

A customer can add a requested delivery date when placing an order. The delivery moment is often specified as soon as possible since spreading fertiliser over land requires specific weather conditions. Because the weather normally becomes more uncertain when looking further ahead, customers want to delay ordering for as long as possible to prevent high inventories. When a customer orders and wants the product as soon as possible, given that the product or raw materials are in stock, the expected delivery date is set along the internal lead times Triferto handles. Customer-specific blends have a lead time of five working days, and all other products have a lead time of three working days as section 2.1.2 explains. Triferto uses this lead time to cover production and other handling activities, which are part of Figure 2.2.

The lead time, which is immediately assigned to an order when it is placed and is solely based on product availability of the facility, can turn out to be too strict. This results in extra actions to meet said lead time which requires extra resources, or the delivery date is delayed. The events of delaying the delivery date of orders are not monitored and are not labelled as nonperforming as long as the customer does not file a complaint about it. Delayed delivery dates are often handled in good consultation with the customer, which results in them not complaining.

The contractual agreement between Triferto and Agrifirm states that 97.5% of all orders should be delivered according to OTIF philosophy. This means that the orders should be delivered exactly on the requested delivery date that comes with the Agrifirm order. There are limitations to the delivery date Agrifirm can request for each order, which depends on what moment the orders are forwarded to Triferto. These delivery date targets will reflect the before-mentioned lead times of three and five days in Section 2.1.2.

In the past, Triferto could often avoid escalation and prevent a complaining customer by consulting with them about finding a solution for not being able to meet the intended delivery date, Triferto now has to deliver Agrifirm orders on the exact requested delivery date with no exceptions. Each Agrifirm order which is not delivered on this date, will not count towards the OTIF target percentage meaning that there is not much room for error since 97.5%

of the orders should be OTIF. When trade-offs need to be made regarding delivering orders on time, Triferto can use a form of order-handling prioritization. Prioritizing Agrifirm over Triferto orders results in Agrifirm orders having a better delivery performance at the expense of a decrease in performance on their orders. While this is appealing to increase the OTIF performance of Agrifirm orders which prevents financial consequences, this might cause structural underperformance.

### 2.3.2 Context In-Full delivery at Triferto

When looking into the In-Full delivery of orders, we should distinguish between the two order types. For bagged goods, the In-Full delivery is relatively simple since the ordered amount can be counted. For example, a customer can order five big bags or 15 pallets of 25kg sacks. This rarely goes wrong since it is normally checked by the forklift operator and the truck driver separately. Bulk product however is more interesting. A customer can order a certain amount of KGs or tonnages for one or more products. This then gets loaded by silo or by shovel in the transportation truck. The goal is to load exactly what the customer ordered, but with these robust machines, it can be a challenge to exactly match this target. In the end, the customer gets an invoice of the exact amount that is loaded, which is ideally as close as possible to the actual ordered amount. Triferto does currently not have any guidelines regarding in-full delivery of bulk orders other than as close as possible to the ordered amount. Also, the difference between the two is not measured. The in-full delivery is measured much like the on-time delivery, namely by the number of complaints Triferto receives about the matter.

The agreement between Triferto and Agrifirm also states delivery requirements regarding the In-Full delivery of the orders that are sent to Triferto. The two main order types, bulk products and big bags/sacks called bagged products, have different criteria for a delivery to be considered In-Full. For orders that contain big bags and pallets of sacks, the amount ordered should be the same as the delivered amount because the units are countable. Only then the order is considered In-Full. For orders that contain bulk products, Agrifirm and Triferto agreed upon an error margin of 200 kilograms for each Agrifirm order. The magnitude of the order does not matter in this case. So, an order is considered delivered In-Full if the actual amount differs by less than 200 kilograms from the ordered amount.

## 2.4 Historical Delivery Performance

Section 2.3.1 and section 2.3.2 explain what the OTIF measure means for Triferto. Triferto and Agrifirm came to the conclusion that a target of 97.5% of all orders delivered OTIF is perceived reasonable, given a one-season set-up period where delivery under-performance by Triferto will not be penalized to adjust operations where needed. The acquisition of the OTIF target of 97.5% is largely based on information coming from the opinions of subject matter experts which is not data-driven. This means that there is a possible risk of there being a gap between what the experts believe is possible and the actual achievable delivery performance. Therefore, it is required to analyse the historical order data to investigate if it is possible to calculate these performance measures of the previous year and see if they are actually in sync with the opinions of the subject matter experts, to set a performance baseline and if the OTIF target set within the agreement is ultimately feasible. Section 2.4.1 and Section 2.4.2 analyse the historical data for both elements of the OTIF delivery performance measure.

### 2.4.1 Historical Performance On-Time Measure

By analysing the historical order data we try to measure the historical performance regarding the on-time delivery of orders. Despite there being distinct identifiers within the data set that should highlight the measure, we are not able to derive the difference between planned and actual delivery moments due to the identifiers being used incorrectly. Triferto does not capture the difference between requested and actual delivery dates (yet). Therefore it is not possible to gain quantitative insight into the historical On-Time performance of how Triferto performed. However, after discussions with stakeholders, we conclude that On-Time delivery of orders is still a significant risk to the OTIF performance and should be closely monitored during the set-up period of the collaboration. Not only the On-Time performance should be monitored but also the causes of delays when the order was not On-Time. This information will be useful to validate current suspected causes and to adjust the improvement focus where needed.

Given that no quantitative historical data is available, we need to build a model that combines the following aspects to estimate the future On-Time performance of in-scope facilities. Also, due to the collaboration a new demand and facility landscape arises of which the expected performance is unknown. We combine the historical order data of this chapter with a forecast to determine the expected demand for 2023. Additionally, we review the literature in Chapter 3 to find methods that improve the model, specifically the loading process specifications since they currently are generally defined by Triferto. Chapter 4 explains the model and its experiments and Chapter 5 shows the expected On-Time performance in different scenarios and features.

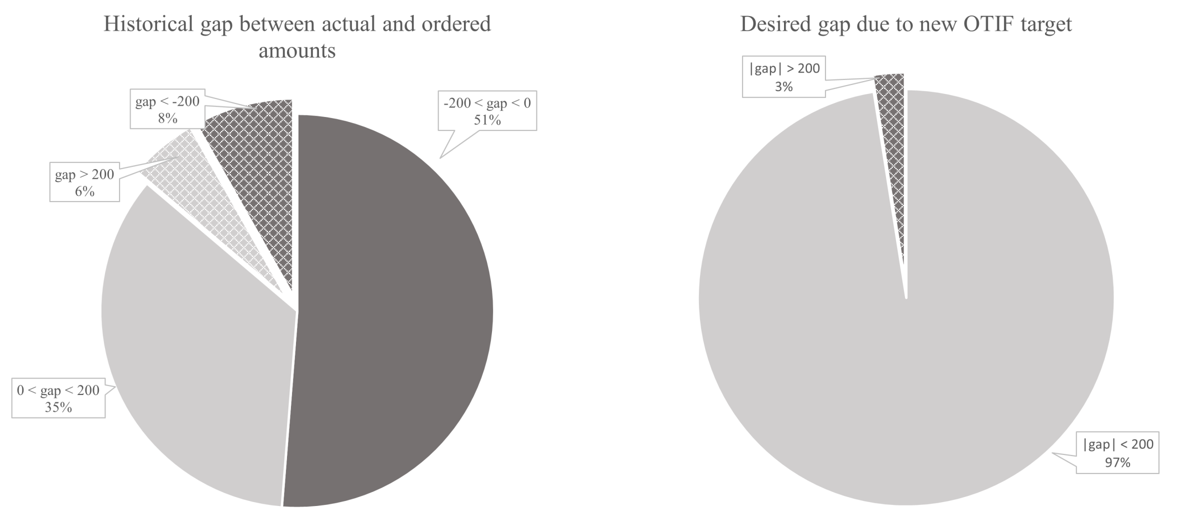
### 2.4.2 Historical Performance In-Full Measure

By analysing historical order data, we study the possibility of determining the historical in-full delivery performance. We make a split between product types regarding the in-full delivery that Section 2.3.2 explains.

**In-Full performance per product type.** First, we address the bagged product category. It is not possible to derive the difference between actual and ordered amounts. Despite the data set containing identifiers that should show the difference between ordered and delivered amounts. However, these are not used correctly and are overwritten after the order is finished by the actual amount delivered due to restrictions of other IT systems like bookkeeping and inventory management. The bagged products are countable and are loaded with a forklift, often in several big bags or pallets. Consultation with stakeholders tells us that there are no problems perceived with the in-full delivery of these bagged orders. Therefore we assume that bagged-type orders are not a risk to the In-Full portion of the OTIF target for next year. Next, we see the following trends regarding the bulk product type. These orders are per definition a risk since the amount delivered can never match the ordered amount exactly. The actual ordered amount is what the customer pays for, so there was no (financial) incentive to carefully load trucks until the collaboration with Agrifirm. Triferto never enforced a maximum gap margin on their bulk orders. The new agreement sets this margin to 200 kilograms as section 2.3.2 explains. The contractual margin was deemed feasible by a selection of facility managers but not supported by quantitative data at the time. However, we find historical bulk orders that identify the gap between ordered and delivered amounts for some specific situations where the delivered amount exceeds the ordered amount. Stakeholders have indicated that the same pattern can be assumed when the delivered amount is less than the ordered amount, which validates the results of analysing the bulk order portion of the data set.

**In-Full and OTIF performance.** Data analysis shows that in 16% of the occasions when Triferto overloaded orders, the gap was larger than 200 kilograms which exceeded the allowed margin. Data limitations cause it to be unmeasurable when for under-loaded orders. We assume the same loading inaccuracy when under-loading orders, which is validated with experts. Figure 2.6a shows a visual representation of the results of the data analysis. This means that a total of 16% of all bulk orders also have a gap larger than an absolute value of 200 kilograms. Bulk orders are generally larger than bagged orders tonnages-wise. Despite the yearly tonnage of bulk orders being larger than bagged orders, the number of bagged orders exceeds the number of bulk orders. This translates to a total of 11% of all orders, bulk and bagged, not delivered In-Full in 2021. This assumes all bagged orders as delivered In-Full. Figure 2.6b gives a visual representation of what portion should be delivered In-Full to adhere to the OTIF target of 97.5%. We see that Triferto, by only considering In-Full performance, has an upper bound OTIF performance of 89% regarding all orders when not considering On-Time performance. This result confirms Triferto's suspicion of expected OTIF under-performance decreases uncertainty and sets a baseline for the future In-Full delivery performance.

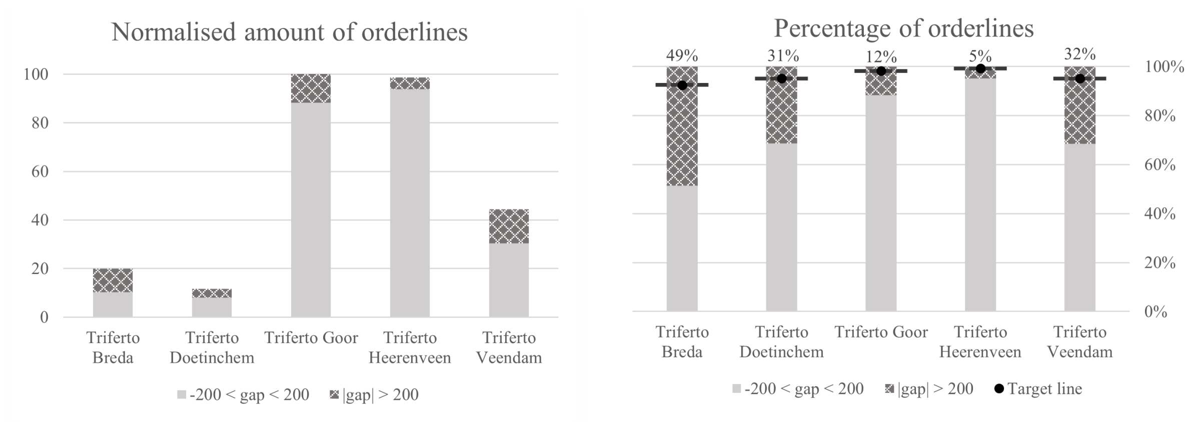
**In-Full performance per location.** There is a notable difference between the In-Full delivery performance among the facilities. Figure 2.7 shows their in-full delivery performance relative to each other. Figure 2.7a shows the normalised number of bulk orders for each facility that are loaded within the allowed error margin (light grey) and the normalised number of bulk orders that exceed the allowed absolute deviation of 200 kilograms (dark grey and white). Figure 2.7b shows the same type of orders as 2.7a, but then as a percentage of the total number of orders handled at the specified facilities. The dashed black line in 2.7b shows the target in percentages for each facility which is required to meet the in-full delivery target of 97.5% while assuming each facility reduces the number of orders that are not considered in-full by 84%.




(a) Percentage of bulk orders within and out of 200 kilograms error margin

(b) Percentage of bulk orders required to be within the margin to meet OTIF target

Figure 2.6: Actual and ordered weight gap - historical and desired situation




(a) Normalised amount of order lines which are within and out of allowed margin per location

(b) Percentages of order lines which are in and out of the allowed margin per location and a line indicating the required percentage of correct orders to meet In-Full target

Figure 2.7: Normalised and percentages of order relative to error margin

The facilities Goor and Heerenveen, which are responsible for 70% of the number of bulk orders, perform significantly better (less than 15% of orders out of margin) than the other three facilities (more than 30% of orders out of margin). The difference in performance originates from the difference in available loading facilities and/or equipment at each location as Section 2.1.3 explains. Triferto knows this and tries to manage this by considering the facilities in determining the product portfolios of each facility. Heerenveen is the best-performing facility with an error of 5%. This is expected since the facility is specialized to this type of order, 86% of the tonnages processed in Heerenveen are of the order category bulk. Goor on the other hand is a more diverse facility which processes essentially the same amount of bulk and bagged tonnes, which still performs better than the other facilities. Also as the data shows for Doetinchem, loading is less accurate (31% compared to 12% of error) likely due to not having direct feedback on how much is being loaded in the truck like in Goor due to the difference in weighing bridges.

## 2.5 Conclusion

In this chapter, we answered the first research question to the best of our ability about determining the historical OTIF performance before the Agrifirm collaboration. An order needs to be both On-Time and In-Full for it to count towards the OTIF score. On-Time and In-Full order specifics are explained in Section 2.3 Also, we partly achieved the first research objective of setting a baseline OTIF performance given the available information by identifying the historical In-Full performance. Lastly, we laid a foundation to reach our second objective of finding factors and their relations that determine the throughput capacity of the loading process by consulting with employees with various roles which will be further built upon in Chapter 3. The main conclusions of this chapter are summarised in the following points:

- **Context analysis:** Triferto's product portfolio can be distilled into two different product categories that are relevant for this research: bulk and bagged fertiliser. The two product types can be seen as separate streams regarding the loading process. The throughput capacity of a facility is the total amount of product that can be shipped from one facility to its customers in a period, given that the final product is in stock. While the loading process is similar at all facilities, factors that determine the throughput capacity differ per location. The main factors that impact the throughput capacity are explained in Table 2.1 according to employees. Specific process times that determine the throughput capacity of the loading process that depends on these factors are also unknown other than the number of loading spots, and throughput capacity per loading spot per facility.

- **Historical OTIF performance:** The target delivery date is not documented within Triferto such that On-Time performance cannot be determined. The In-Full performance of the bagged category could not be analysed. This however is not perceived as a risk by Triferto since little to no errors are made in this process. Bulk In-Full performance is measurable for orders where delivered amounts exceed the orders amounts, which allows us to approximate it for all Bulk orders. 86% overall bulk orders are within the 200 kilograms error margin with respect to the 97.5% target. This results in an upper bound OTIF performance of 89% of all orders in 2021. Performance can be assessed per facility. There is a large difference amongst facilities, the most extreme being 51% in Breda and 95% in Heerenveen as shown in Figure 2.7.

Additional research is required and a model is needed for the loading process that uses throughput capacity to fulfil orders to assess On-Time performance. Triferto lacks process information and a method to estimate future On-Time performance over her facilities in different scenarios. The next chapter reviews the literature to study the relation between throughput capacity and delivery performance, and to find additional insights into loading processes that build on the context analysis of this chapter to lay a foundation for building a simulation model in Chapter 4. Also, the next chapter studies similar cases and how they are solved within the available literature, and judges simulation modelling as a suitable solution approach for the problem of reducing the uncertainty of the impact of throughput capacity on the On-Time delivery performance.

# Chapter 3

# Literature Review

This chapter answers research question two which is about the relation between delivery performance and throughput capacity, the impact of throughput capacity on On-Time delivery performance, and studying similar business contexts. Section 3.1 studies the relation between throughput capacity and delivery performance to strengthen the review made by Triferto about throughput capacity impacting delivery performance. This section also discusses adaptive capacity management and its potential for this research. Next, Section 3.2 consults literature with similar business context to get a better understanding of loading processes and find information that is relevant to include in our own model described in Chapter 4. Next, Section 3.3 explains simulation as a method to model the logistical process. Lastly, Section 3.4 explains the importance of a conceptual model and describes the core activities of making one.

## 3.1 Relation Delivery Performance and Throughput Capacity

The first part of this section delves into relevant literature, elaborating on the correlation between throughput capacity and delivery performance. The objective is to review the statement put forth in Section 1.3.1, wherein supply chain experts indicate the significance of insufficient throughput capacity as a key factor leading to delayed deliveries. In the last part, we dive into a specific method that adaptively handles available capacity to cut down on lateness in deliveries. This technique has the potential to optimise the loading process and is further examined through modelling in Chapter 4.

Gunasekarana (2004) developed a framework that promotes a better understanding of supply chain management performance measurements and metrics. On a strategic level, the framework states that order lead times are one of the more important performance metrics within a supply chain. Lower lead times lead to a reduction in supply chain response time, which is a source of competitive advantage. Lower lead times also have a positive effect on customer satisfaction due to faster delivery times(Christopher, 1992). The framework of Gunasekarana (2004) explains that capacity flexibility is important on a tactical level. According to Slack et al. (2003), a higher capacity flexibility has a positive impact on response to customer demand, lead times and deliverability. To add, Bradley and Arntzen (1999) who researches the planning of multiple company assets within seasonal demand environments, like the fertiliser industry, concludes that adding capacity can lead to increased return on operating assets. On the operational level, they identify the two most important measures of delivery performance, which are the quality and the On-Time delivery of goods. Both link to the metric of the perceived value of the product by the customer. Maskell (1991) suggests that companies should understand that day-to-day distribution operations are often handled with non-financial measures that capture the essence of process performance.

Job shops are commonly found in small manufacturing systems where orders pass through multiple machines (Land et al., 1999). This logistical process shares similarities with the research at hand. A job shop system comprises multiple stations (loading spots), order types with specific restrictions, and varying arrival rates. In the cited study by Land et al. (1999), various approaches for enhancing delivery performance in a job shop environment are explored. The methodology that aligns with the context of throughput capacity and improving On-Time performance involves reducing lateness by reactively adjusting capacity during periods of high workload. The findings indicate that a significant reduction in lateness can be achieved by increasing capacity when the current capacity usage reaches a certain threshold. Determining the optimal capacity increase and the workload level that triggers this adjustment involves a trade-off between resource utilization and benefits gained. According to the research, the most effective configuration involves a 20% capacity increase triggered when the current capacity reaches 85% of its threshold. This adjustment leads to a reduction in the lateness of around 20% in different scenarios. Thus, a relationship between throughput capacity and delivery performance is established, highlighting the positive impact of capacity flexibility on On-Time order delivery, as previous literature suggests.

## 3.2 Determining Factors of Truck Loading Processes

This section considers multiple studies that contain information about similar logistical processes as the one within this research. These studies mention important factors that determine logistical throughput capacity in truck-loading environments. The vast majority of literature about bulk truck loading activities is in marine terminals (Wahyudi and Pujawan (2020), Neagoe et al. (2021), David and Collier (1979)) and mining sector (Lizotte and Bonates (1987), Runciman et al. (1997), Park et al. (2016)). Chagas et al. (2020) study the loading process of full trucks at a large fertiliser production facility with multiple loading docks. These studies all consider bulk products like coal, iron, wheat and fertiliser. Nedvědová et al. (2019) research a system containing pallet loading activities, to estimate maximum flow through a large area with multiple warehouses. This section discusses these studies and cites factors related to the loading process that fit in the context of this research with the intention of incorporating them into the simulation model as Chapter 4 describes. This is to enhance the initially basic simulation model.

The most reoccurring factor that determines the loading capacity we find within the literature is the capacity of the loading equipment itself, like marine cranes, shovel machines, hatches/silos, and forklifts. Wahyudi and Pujawan (2020) find that 52% of time spent in their logistical process of unloading ships intro trucks is loading preparation (29%) and loading time (23%). How loading capacity is included within these studies is done in different ways. Multiple studies use different distributions to determine the loading time of a full truck in their model fitted to time measurements of the system, like Normal (Wahyudi and Pujawan (2020)) and Weibull (Lizotte and Bonates (1987)), Runciman et al. (1997) also uses Weibull and Beta distributions to determine loading times in their model based on another mine using the same loading system, which is a big chute. Park et al. (2016) uses a uniform distribution with a minimum and maximum loading time between 2.5 and 3.5 minutes. The use of distributions to determine loading time implies that there is variability in the loading speed of said equipment since it considers the same truck capacity within the studies. Other studies assume constant loading capacities per time of time for loading equipment. Chagas et al. (2020) considers multiple docks in their premises that have different loading capacities amongst each other. Neagoe et al. (2021) considers a conveyor belt system that loads trucks from above, which has a set maximum capacity. For pallet loading, Nedvědová et al. (2019) uses a setup time of 7 and a constant loading time of 1 minute per pallet in a warehouse setting within temperature-related environments. Besides the capacity of previously mentioned systems, the number of said systems available in the process also has an impact on the loading capacity in most cases.

Besides loading equipment capacity, the available literature also provides insights into other factors that are important for the logistical process of loading trucks. According to Wahyudi and Pujawan (2020), internal travel distances also have a great impact on their maritime system, which is over 30% in their specific case. While loading with forklifts, David and Collier (1979) concludes that the distance between the loading position and product location, and the number of forklifts servicing the loading position are part of the function determining throughput capacity. Lizotte and Bonates (1987) also show in their results that internal travel times have an impact on the process at hand. Experiments show that by decreasing internal travel times from 125% to 75%, the productivity of the whole system increases between 4% and 6% depending on what dispatching rule is used. Neagoe et al. (2021) incorporates a weighing bridge in their logistical process, which uses a constant weigh-in time of 1.5 minutes and a weigh-out time that follows a normal distribution with a mean of 3.46 and a standard deviation of 1.63 minutes.

The contents of this section focus on process performance measures like truck utilisation, system throughput, loading equipment utilisation, idle time, truck waiting time, and environmental impact. Demand in these studies is often defined as a push of large amounts of products like ships that need multiple truckloads of unloading, mines that continuously generate resources, or factories that produce and push out a product that needs dispatching. This mostly concerns full truckloads. Also, the scale in terms of tonnages and size of facilities is often much larger than that of the research context. This differs from the research at hand that considers a more customer-demand-driven scenario. This includes varying order sizes, irregular order arrival moments and order sizes, heavy seasonality, and delivery performance as the main performance indicators. However, this review shows the relevance of secondary activities like internal travel times on the throughput of a system and gives a foundation on how to implement stochasticity in the simulation model to further enhance it.

## 3.3 Simulation modelling of truck loading processes

In this section, we assess simulation as a modelling technique for this research. First, we generally asses simulation and its different types within the broad scope of transport modelling. Then, we assess the studies within the previous sections, which lie close to the research at hand, on the use of simulation. The objective is to consolidate the use of simulation within this research as a method that fits the problem.

Simulation is accepted in the literature to study complex systems that prove to be numerically unsolvable due to huge computational time limitations. The complexity, stochasticity and unclear relations between in- and output variables of a problem make simulation a fit to analyse it (Law, 2015). Simulation modelling is frequently used for transportation system modelling, which often uses a kind of (truck) loading process. Branislav Dragovic et al. (2016) analyses 226 papers of which 209 make use of simulation modelling of port and/or container terminal operations that often have interfaces or similarities with (un)loading processes. Discrete-event simulation remains one of the most popular techniques in this field. More than 20% of the simulation studies were done in ARENA, which is a discrete-event simulation program, despite the introduction of new techniques like agent-based modelling, network-based modelling, and so on. ARENA uses discrete-event simulation to create a digital twin by using historical data of which the results are vetted against actual systems results (Rockwell, 2023). In discrete simulation models, the time variable is discrete. This means that variables of the system remain constant and change value only at discrete points in time called events. Between any two events, the state of the system remains the same. Thus, to represent the changes in the system over time it is only required to describe the actions of each event and at what time they happen (Seila, 1995). In a continuous system, the state variables change continuously with respect to time. Normally, a system does not solely have discrete or continuous processes but often has one predominant type. Therefore, it is possible to label a system as discrete or continuous. The two types can also be combined within a simulation study. In a discrete event simulation, continuous processes can be controlled by differential equations and are updated each time an event happens (Nutaro, 2007). Agent-based modelling is used to model systems with many individuals who each have certain characteristics that do actions and have interactions to understand their behaviour and outcomes. Agent-based modelling is used to study for example human systems and traffic systems that have many individual entities called agents who interact with one another(González (2008), Bonabeau (2002)).

In the more specific case studies analysed in Section 3.1 and Section 3.2, simulation is also the predominant method of evaluating the performances of these systems. 8 out of 10 use simulation modelling, and 5 studies explicitly mention the use of discrete event simulation. Reoccurring motivators to use simulation in these studies are the increasing flexibility and animation capabilities of simulation software throughout the years (Runciman et al., 1997), and the potential to dynamically represent reality (Lizotte and Bonates, 1987). An additional motivator is the ability to test multiple scenarios without affecting daily operational performance (Wahyudi and Pujawan (2020), David and Collier (1979)), like capacity management methods (Land et al., 1999), different truck dispatching rules (Lizotte and Bonates, 1987), and comparing the impact of various congestion management initiatives (Neagoe et al., 2021).

The analysis of the broad research scope and the assessment of the studies cited in Section 3.1 and Section 3.2 show that simulation is a frequently occurring modelling technique. Discrete event simulation is the predominant type and is used in studies that resemble the most with the research at hand. Simulation gives the ability to test multiple scenarios and features without affecting daily operations. These scenarios can be designed to resemble future demand/facility settings, can add stochasticity to further enhance the validity, and give insight into the expected impact of optimisation techniques.

## 3.4 Conceptual Modelling

Conceptual modelling is the abstraction of a simulation model from the part of the real world it is representing. A complete conceptual model states what to model, and what not to model (Robinson, 2015). A conceptual model is not always explicitly documented and can remain within the modeller's mind. However, there are several benefits of documenting such a model. Some of these benefits are; 1) help to minimize the likelihood of incomplete, unclear, inconsistent & wrong requirements, 2) building the credibility of the model, 3) guide experimentation by expressing modelling objectives, inputs & outputs, 4) and builds a consensus about the nature of the model and its use. Robinson (2008) outlines a conceptual modelling framework we use for this research. Conceptual modelling involves five core activities that are performed roughly in the following order:

1. Understanding the problem situation
2. Determining the modelling and general project objectives
3. Identifying the model outputs
4. Identify the model inputs
5. Determining the model content (scope and level of detail), identifying assumptions and simplifications

These activities and documenting the findings following the previously mentioned framework (Robinson, 2008) result in a set of tables that describe each element of the conceptual model. These tables describe the following points:

- *Modeling and general project objectives*: Identifying the overall aims of the organisation and how the model contributes to achieving them by setting model objectives. Also, determining general project objectives of the model like time-scale, run-time and usability.
- *Model outputs/responses*: Identifying outputs that show whether modelling objectives are achieved (or not).
- *Experimental factors*: Experimental factors are a limited subset of the general input data that are required for model realisation and can be changed in order to achieve modelling objectives.
- *Model scope*: Addressing the four main components of the process and if they should be included within the simulation model: entities, activities, queues and resources.
- *Model level of detail*: Deciding the amount of detail to include for each component in the model scope. Are made with reference to; consultation with stakeholders & judgement of the modeller, past experience of the modeller, data analysis and prototyping.
- *Modeling assumptions & simplifications*: Determining the scope and level of detail of the model brings various assumptions and simplifications. Assumptions are made when there are uncertainties or beliefs about the real world that need to be included in the model. Simplifications are incorporated to enable timely development and decrease model complexity.
- *Data requirements*: Determining what data sets from the organisation are required for model realisation and validation.

## 3.5 Conclusion

This chapter provides a review of the relevant literature for this research by answering the second research question and adding to the context description. The literature gives multiple indications and examples of the relationship between delivery performance and throughput capacity. Next, a more specific literature study about problems that resemble the context of this research explains how logistical throughput capacity is embedded in various systems, and what factors have a significant impact on their performance. Also, some specific processes found in these cases give detailed process data that can be used in the simulation model of this research. Lastly, the use of simulation within logistical processes is studied within the literature and why this fits this type of study well. The main conclusions of this chapter are summarised in the following points:

- Capacity flexibility has a positive effect on lead times, which in turn positively affects customer satisfaction and competitive advantage. A method used by Land et al. (1999) shows that reactively in- and decreasing available capacity leads to an order lateness reduction of up to 23% in that specific case.

- The most important factor that determines the logistical throughput of a system often is the throughput capacity of the loading equipment itself. The available number of said equipment also has an impact. Also, more detail is given about how logistical throughput is modelled within these cases than Triferto has available, like loading speed and weigh-bridge times. However, most of the related studies are on a scale that is significantly bigger than the context of this research. This results in secondary processes like internal travel times having a significant impact on total throughput.

- Various studies use different distributions to model the loading process that has similarities with the research at hand. With this information, we can add to the basic model and research the impact of including such stochasticity via distributions on the logistical system's expected performance. Specifically, we study a Weibull distribution for secondary activities and normally distributed loading speeds in Chapter 4.

- Simulation modelling is widely used within transportation and logistic system modelling, of which discrete event simulation is the most predominant simulation type. 8 out of the 10 specific case studies related to the research context use simulation modelling, and 5 studies explicitly mention the use of discrete event simulation. The key motivator to use discrete event simulation within this research is the ability to test multiple scenarios without affecting daily operational performance.

In the next chapter, we combine the context analysis of Chapter 2 and the findings of reviewing the available literature about similar logistical processes in Chapter 3, to build a simulation model that can assess the expected On-Time performance of the in-scope facilities in different scenarios by experimenting with the logistical throughput capacity and the factors that determine it. Simulation fits the objective of experimenting and assessing system performance within this context and the process details of Section 3.2 can be used to fill in the missing data gaps Triferto has in her logistical processes. Also, the adaptive capacity flexibility can be tested within the simulation model to see if it positively affects the On-Time performance of orders.

# Chapter 4

# Simulation Model and Experimental Design

This chapter describes the model used to assess the On-Time performance of Triferto's facilities in different scenarios including future demand settings and optional optimisation features. Section 4.1 explains the input parameters used within the model. Next, Section 4.2 describes the outputs after running the simulation model with experiments that Section 4.3 designs and explains. This simulation model is programmed in Siemens Tecnomatrix Plant Simulation©, which is a discrete event simulation program. Prior knowledge of the main researcher and findings of Section 3.3 are the main reasons for the selection of this program. Appendix B describes the conceptual model used in this chapter that follows the method described in Section 3.4. Appendix D explains the considerations regarding verification and validation of the simulation model. Lastly, Section 4.4 surmises the main limitations of the final model.

## 4.1 Input for Simulation Model

This section describes the different inputs for the simulation model, how they are determined, and how they are implemented in the model. Figure 4 shows the order flow of orders through the logistical system. At each of the main process steps, a list is given of important topics related to that process step. These topics include important model inputs, model outputs, variables, process characteristics, and experimental factors.

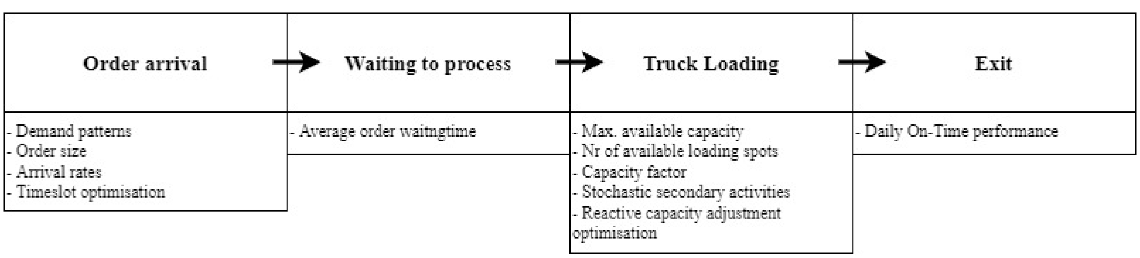



Figure 4.1: Simulation model with important topics discussed in Chapter 4

### 4.1.1 General settings

**Run-time.** The facilities operate a single shift from 8:00 to 16:00, 5 working days a week. This means there is an operating time of 8 hours each day. This is also the time window when orders can arrive in the system. However, the working day truly ends when all orders that came in that day are fulfilled. This means that overtime can be required to fulfil all orders. More on the order and demand generation can be found in the next section. We consider 260 working days per year, which is a single simulation run. We are interested in the performance over this period of time, and not the steady state of the system. This means that we have a terminating simulation, which means no warm-up period is required. Additionally, the daily reset of the system also results in not requiring a warm-up period.

**Number of replications.** Multiple runs per experiment using their unique seed value are required to estimate the mean of the main output variable with a specified error or precision. We use the method described in Law (2015) to find the number of replications required to estimate the mean with a confidence interval with $\alpha = 0.05$. This means that there is a 95% chance that the true mean lies within the confidence interval. Table 4.1 shows the number of replications required for each of the original facilities. Configurations used in the tests are the ones that give a late delivery percentage of around 5% for each facility. There is a large difference between the number of replications required for each facility. However, computational times are manageable, and therefore we use 22 replications per experiment for each facility.

| Facility | Required number of replications |
|---|---|
| Breda | 22 |
| Doetinchem | 7 |
| Goor | 16 |
| Heerenveen | 8 |
| Veendam | 6 |

Table 4.1: Required number of replications required to meet desired result accuracy per facility

### 4.1.2 Demand data

**Weekly demand tonnages.** Forecast for 2023 based upon historical demand data and expected Agrifirm demand serve as input for the demand generation in the simulation model. Within the model, weekly demand is specified in the number of tonnages per week, which is divided by 5 to determine the average daily demand for that week. A new weekly demand data set can easily be loaded into the model to reflect other scenarios like demand/season fluctuations, which makes the model usable beyond the scope of this specific research. But arguably the company will never use Plant Simulation due to expensive licensing.

Specifically for this case, we use the demand from 2021 as a naive forecast to simulate the Triferto demand for 2023. We combine this with the 2023 forecast from Agrifirm to determine the weekly demand for 2023 per facility. This assumes that the distribution of Agrifirm orders, which is based upon the first months of the collaboration, will stay the same during the rest of 2023. One adjustment is made in consultation with stakeholders. This adjustment moves 3% of demand from Drachten to Heerenveen. Yearly demand data of Drachten and Oss is available, but distribution over the weeks based on historical trends is not due to Triferto not operating the facilities in the past. Therefore the two locations cannot be modelled without a weekly demand distribution.

**Order arrivals.** To determine the arrival rate of orders in the system, we use the daily demand and the order size characteristics. The distributions mentioned in the section above result in an average order size for each product category. Dividing the daily tonnages per product type by the accommodating average order size results in the average number of orders for that specific day per product group. We assume an independent arrival of orders throughout the day the facility operates. The model uses the Poisson arrival process that embraces this independence of arrivals. Therefore we determine the interarrival time by drawing samples from the exponential distribution with a mean of the average interarrival time in seconds. This mean is calculated by dividing the daily working time in seconds by the average expected amount of orders for that day.

**Single order size characteristics.** When an order arrives, the size needs to be determined and lies between 0 and 35 tonnes. The distributions of order sizes differ per order type, so two different distributions are used within the model to determine the order size. Due to order patterns specific to the fertiliser sector, it is hard to fit a single distribution to fit the order size. We test exponential, Gamma, and Weibull distributions to fit the data. Appendix C.1 shows the comparison between historical order size and the sizes the model generates. For bulk orders, an empirical distribution is used that is based on historical order data as Figure C.1 depicts. The distribution for bagged order sizes uses a Weibull distribution ($\kappa$ = 0.81 and $\lambda$ = 3.69) to determine the size between 0 and 24 tonnes, which represents 92.6% of all bagged orders. The other portion with the range of 23 to 35 tonnes uses an empirical distribution. Figure C.2 indicates the distribution split used in the bagged order size distribution and the comparison between the historical and modelled sizes.

### 4.1.3 Throughput Capacity data of Loading process

The factors that impact the available throughput capacity of the loading process determine how quickly an order can be processed. Section 1.3.1 explains throughput capacity and shows some factors that Triferto regards as important to the impact of it. Additionally, Section 3.2 studies literature with similar context that validates some of the factors pointed out by Triferto and identifies potential factors Triferto did not consider in the first place like internal travel times. Triferto does not have or collect any data on these individual processes and therefore provides a simplified version of characteristics that are used in the model. These are the number of available loading spots per product type and the maximum capacity of these loading spots in tonnages per second. After Section 4.3.3 we include more stochasticity to the model in addition to order arrivals and order size by adding distributions to the loading process speed and secondary activities based on the literature review in Chapter 3. Table 4.2 shows the standard setup for each facility by showing the number of loading spots and the normalised capacity of an individual loading spot per facility. Triferto also decreases its available capacity during the year due to heavy seasonality and varies between different levels throughout the year as Figure 2.5 shows. Table 4.3 shows the percentage of available capacity per product group for the periods of the year. This capacity management is done by Triferto throughout the year and used in their general capacity calculations.

| Facility | Nr Bulk Spots | Bulk Capacity | Nr Bagged Spots | Bagged Capacity |
|---|---|---|---|---|
| Breda | 1 | 57 | 2 | 75 |
| Doetinchem | 1 | 86 | 2 | 75 |
| Goor | 1 | 100 | 2 | 75 |
| Heerenveen | 1 | 100 | 2 | 75 |
| Veendam | 1 | 86 | 2 | 75 |
| Drachten | 1 | 100 | 0 | - |
| Oss | 1 | 100 | 1 | 100 |

Table 4.2: Standard loading process characteristics per facility

| Period in weeks | Available Cap.% Bulk | Available Cap.% Bagged |
|---|---|---|
| Begin-4 | 58% | 59% |
| 5-17 | 100% | 100% |
| 18-30 | 58% | 59% |
| 31-End | 44% | 31% |

Table 4.3: Capacity level in relation to maximum available capacity throughout the year per product type

## 4.2 Output of Simulation Model

The simulation model's output is the data obtained after each experiment that gives insight into the performance of that particular loading process setting or demand scenario. There are multiple outputs that give insight into this performance. The main goal of the simulation model is to assess its On-Time delivery performance. An order is handled On-Time when it is finished before the end of the day plus its own process time determined when an order enters the system. This is to prevent falsely counting orders as not On-Time that come in just before closing time when there was no chance of handling them in regular production time. The main Key Performance Indicator (KPI) of the model is the percentage of orders that are delivered On-Time. Generally, this is measured in a time period of a year, since the OTIF delivery target is set to 97.5% annually. However, the model also gives insight into weekly performance to assess capacity use. Table 4.4 gives an overview of the most important outputs of the simulation model, in what unit they are measured and why they are included. They are measures per facility per product group and can be assessed on a yearly or weekly basis.

| Output measure | Unit of measure | Explanation |
|---|---|---|
| On-Time score | %On-Time of all delivered orders | Main KPI, to assess the On-Time performance |
| Demand | Tonnages per product group | Insight into total demand and seasonality |
| Capacity | Tonnages per day per product group | To assess capacity utilisation throughout the year |

Table 4.4: Most important simulation outputs to assess logistical process setting or scenario performance

## 4.3 Experimental Design

The following sections show the design of experiments to test various sets of settings and implementations. First, we run the model in the most basic setting to set a baseline as Section 4.3.1 explains. Next, Section 4.3.2 explains a sensitivity analysis to find settings for each facility so that they meet the On-Time target performance and study what impact the number of loading spots has on it. Then, we test the impact of having a adaptive capacity adjustment as Section 4.3.3 describes. Next, Section 4.3.4 studies the effects of stochasticity on the performance to enhance the model. Here we combine qualitative information coming from Triferto and findings of Section 3.2. Lastly, Section 4.3.5 designs experiments to support Triferto in its decision to introduce timeslots within its organisation. Due to computational time limitations, not all experiments can be rigorously tested. Settings and facilities chosen within the experiments are carefully selected to draw meaningful conclusions regarding the goal of said experiments.

### 4.3.1 Baseline performance

Triferto uses a uses loading speed for each loading spot per product category. Table 4.5 shows the set of experiments that result in the expected performance for each facility with their standard setting. The capacity factor is a multiplier applied to the initial loading speed defined by Triferto. This capacity factor times the actual loading speed of a loading spot at a point in time is the loading speed used in the experiment for that day. When we set this factor to 1.0 and use the default number of loading spots per category, we assess the performance of all facilities as Triferto initially defined them in their yearly loading capacity calculations. The results of these experiments and their On-Time performance are used to assess the performance of other experiments within the chapter.

| Experiment | Facility | Nr of Bulk spots | Capacity factor Bulk | Nr of Bagged spots | Capacity factor Bagged |
|---|---|---|---|---|---|
| A1 | Breda | 1 | 1.0 | 2 | 1.0 |
| A2 | Doetinchem | 1 | 1.0 | 2 | 1.0 |
| A3 | Goor | 1 | 1.0 | 2 | 1.0 |
| A4 | Heerenveen | 1 | 1.0 | 2 | 1.0 |
| A5 | Veendam | 1 | 1.0 | 2 | 1.0 |
| A6 | Drachten | 1 | 1.0 | - | - |
| A7 | Oss | 1 | 1.0 | 1 | 1.0 |

Table 4.5: Experiments resulting in expected performance of all facilities

### 4.3.2 Sensitivity Analysis

By establishing a baseline performance for each facility, we can distinguish the facilities that are meeting the required standards from those that require further attention. Since the two product categories have their own loading process and are independent, the performance of each product type can be assessed individually and there is no coherence between each product category's performance. With this performance, we can design a set of experiments per facility that tests a range of capacity factors to reach the On-Time delivery goal of 97.5%. Table 4.6 shows the settings of Breda to find the optimal setup based on the results of its baseline performance. Similar experiments are done for each other facility. Doing these experiments for each facility results in a setting that meets the yearly On-Time target of 97.5%.

| Experiment | Facility | Capacity factor Bulk | Capacity factor Bagged |
|---|---|---|---|
| B1 | Breda | 0.4 | 0.8 |
| B2 | Breda | 0.5 | 0.9 |
| B3 | Breda | 0.6 | 1.0 |
| B4 | Breda | 0.7 | 1.1 |
| B4 | Breda | 0.8 | 1.2 |
| B4 | Breda | 0.9 | 1.3 |
| B4 | Breda | 1.0 | 1.4 |
| B4 | Breda | 1.1 | 1.5 |

Table 4.6: Experiments for Breda assessing the impact of raw capacity decrease/increase

We also assess the total available capacity for each scenario to see if increasing the number of loading spots and decreasing the available capacity can lead to better On-Time performance while utilising less or the same total capacity tonnage-wise. Increasing the number of loading spots from 1 to 2 without decreasing capacity per spot, results in doubling the total capacity. To combat doubling the total available loading capacity, capacity factors are adjusted when increasing the number of loading spots to study the effectiveness of increasing loading spots while keeping the same total available capacity. Therefore, the total available capacity throughout the year and its utilisation become more critical than in previous experiments. There are already multiple loading spots for Bulk in reality, but due to data limitations and complexity, Triferto simplified this in their capacity calculations and uses 1 spot for each of their facilities in their capacity calculations and this model. While the model allows testing with the number of loading spots for both product types, we only test adjusting the input variable for the Bagged product type due to its relevance. Table 4.7 shows the experiments to study the impact of adjusting the number of loading spots for Bagged products at the facility in Breda.

| Experiment | Facility | Capacity factor Bulk | Capacity factor Bagged | Nr of Bagged spots |
|---|---|---|---|---|
| C1 | Breda | 0.7 | 1.8 | 1 |
| C2 | Breda | 0.7 | 2.0 | 1 |
| C3 | Breda | 0.7 | 2.2 | 1 |
| C4 | Breda | 0.7 | 1.0 | 2 |
| C5 | Breda | 0.7 | 0.56 | 3 |
| C6 | Breda | 0.7 | 0.66 | 3 |
| C7 | Breda | 0.7 | 0.76 | 3 |
| C8 | Breda | 0.7 | 0.4 | 4 |
| C9 | Breda | 0.7 | 0.5 | 4 |
| C10 | Breda | 0.7 | 0.6 | 4 |

Table 4.7: Experiments for Breda that study the effect of a varying number of loading spots

### 4.3.3 adaptive capacity adjustment

In this section, we describe a set of experiments that study the effect of reactively adjusting capacity during periods of high demand. Note that this is not the same as the seasonal capacity management of Triferto as Table 4.3

explains. Section 3.1 describes a method by Land et al. (1999), which adjusts capacity during high-demand periods in a job shop environment and observes significantly improved delivery performance regarding the lateness of orders. In that study, a capacity utilisation threshold determines the moment the capacity is increased. When the daily loading capacity utilisation reaches a lower threshold again, the capacity is scaled down again to the original amount set in the experiment. For this research, we compare the capacity threshold percentage with the daily capacity utilisation. When this utilisation exceeds the threshold, the capacity is increased by the capacity increases factor for that particular product type. The set of experiments in Table 4.8 studies this methodology by doing a sensitivity analysis of the parameters of this capacity management method. We take both the baseline setting (A7) of Section 4.3.1 and the setting that meets On-Time explained in Section 4.3.2 and shown in Table 5.2 of Oss to test this method, due to the baseline not performing very well regarding On-Time performance. Therefore we expect to see more variation in improvement results than assessing a baseline scenario of a facility that already performs quite well. To verify this, we also test this set of experiments with Goor, which has a better baseline performance.

| Experiment | Capacity increase util. threshold | Capacity return util. threshold | Capacity increase factor |
|---|---|---|---|
| D1 | 0.80 | 0.70 | 0.1 |
| D2 | 0.85 | 0.75 | 0.1 |
| D3 | 0.90 | 0.80 | 0.1 |
| D4 | 0.80 | 0.70 | 0.2 |
| D5 | 0.85 | 0.75 | 0.2 |
| D6 | 0.90 | 0.80 | 0.2 |
| D7 | 0.80 | 0.70 | 0.3 |
| D8 | 0.85 | 0.75 | 0.3 |
| D9 | 0.90 | 0.80 | 0.3 |

Table 4.8: Experiments for each facility of various settings regarding adaptive capacity adjustments

### 4.3.4 Stochasticity in loading process

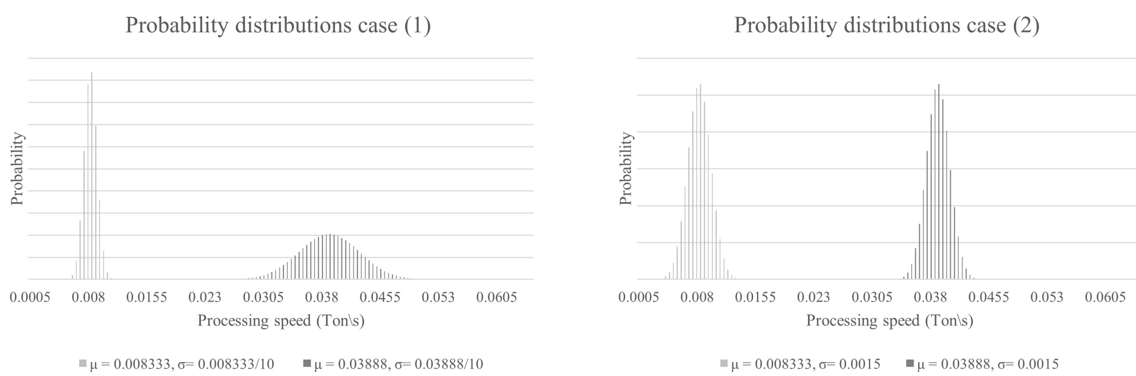
Until this point, all experiments experience a deterministic process time that depends on the order size, capacity increase factor, seasonal capacity factor, and base loading speed of specific order types. In reality, however, loading speeds and the time it takes to handle an order can vary despite orders having similar characteristics. Triferto indicates that there is time variability in different processes like check-in and the loading process. However, they do not collect any process data that quantifies this variability. In the literature described in Section 3.2 we find that in similar studies as this one variability within loading processes is modelled differently. The following list shows the different expressions of loading processes used within these studies.

- Normal distribution (Wahyudi and Pujawan, 2020)
- Weibull distribution (Lizotte and Bonates, 1987), (Runciman et al., 1997)
- Beta distribution (Runciman et al., 1997)
- Uniform distribution (Park et al., 2016)
- Deterministic/Constant (Chagas et al., 2020), (Neagoe et al., 2021), (Nedvědová et al., 2019)

In many of these studies, the context is about loading full truckloads with bulk products. In Triferto's case, however, orders of varying sizes are loaded each day. This means that we can not directly take over these studies and that we need to combine the findings of the literature review and Triferto's qualitative inputs. We implement two forms of stochasticity related to the loading process that are explained, together with their experimental design, in the sections below.

**Normally distributed loading speeds.** Having deterministic loading speeds is unrealistic. Some practical examples of variable loading speeds within the context of Triferto are as follows for each product category. When loading bagged orders, the distance of the storage location and loading spot impacts the travel time for each movement to get a pallet or a set of big bags. This distance varies for each product and loading spot, which leads to varying loading speeds. This is heavily noticeable at the facility in Goor since they have a relatively long and narrow canopy where bagged products are stored. Additionally, Triferto indicates that the skill of the forklift operator also impacts the loading speed. The bulk loading process is simplified in the model, due to Triferto indicating that it not being a risky product category. There is no distinction between normal and blend orders, and silo and manual loading. In reality, these factors also cause the loading speed of bulk orders to vary. Therefore, studying the impact of the variability of the loading speed can result in valuable insights regarding the systems' performance.

We implement stochasticity of the loading speed by making it normally distributed. This keeps the initial average loading speed used by Triferto as the mean but introduces variability as the standard deviation. Wahyudi and Pujawan (2020) also uses a normal distribution to model the truck-loading process. We test two different implementations of the normal distribution as Figure 4.2 depicts. The mean of the normal distribution is the same as the initial loading speeds used in the experiments mentioned above. In case (1), Figure 4.2a shows the probability distributions of low (bagged) and high (bulk) occurring loading speeds where the standard deviation is modelled as a fraction of the mean. In case (2), Figure 4.2b shows the probability distributions of the same loading speed means where the standard deviation is a constant amount. Since there is no available process data, we test a wide range of standard deviations to assess the impact on the systems' performance.




(a) Case (1)

(b) Case (2)

Figure 4.2: Examples of normally distributed loading times of case (1) and (2)

**Including secondary activities within the on-site logistical process using the Weibull distribution.** Secondary activities are the activities that are not directly part of the loading process but are part of the whole on-site logistical process when a truck arrives as shown in Figure 2.4. In prior experimental designs, these activities are included in a simplified manner. Triferto uses constant loading speeds, which 'include' activities like check-in, truck weighing and truck movements on the facilities. This means that the true loading speed of an order is higher than the value used in the model. Again, these secondary activities have no quantitative data that indicate their characteristics. However, consultation with facility managers gives an indication of what these activities can look like. To prevent laying assumptions of each individual secondary process, which decreases the validity of the model, we decide to include these secondary activities as an additional process time drawn from a Weibull distribution for each order.

The characteristics of the Weibull implementation fit the problem context. The loading process heavily depends on the order size, whereas the secondary activities are much less or not dependent on the order size. Figure 4.3 shows the Weibull probability distribution that is considered the base distribution for this implementation with a shape ($\kappa$) of 1.7 and size ($\lambda$) of 3.4. The expected value ($\mu$) of this distribution is 3.0. This is less than the time indicated by facility managers. This is due to it being dependent on arriving trucks, and not orders. In reality, multiple orders are picked up by a single truck. However, in the model orders arrive individually. Therefore, adding this extra time for secondary activities to each order would result in allocating too much secondary process time. The shape of the Weibull distribution, the right skew as Figure 4.3 shows, also fits the quantitative description of these activities of 'it often being around the mean, but occasionally quite some time longer'. Lizotte and Bonates (1987) model their loading process as a 3-parameter Weibull distribution. The third parameter, $\gamma$, represents the location of the Weibull distribution. In their case of loading full trucks, this starting location can represent a relatively constant part of the loading process. In our case, this constant part can reflect the loading time per order, which is determined by the load speed of that moment and order size. So essentially, the loading time determined by the loading speed and order size represents this third Weibull parameter $\gamma$. We also test the impact of adding a constant 3 minutes of processing/loading time, the expected value of the distribution at hand, to purely check the effect of the stochasticity of the secondary activities.

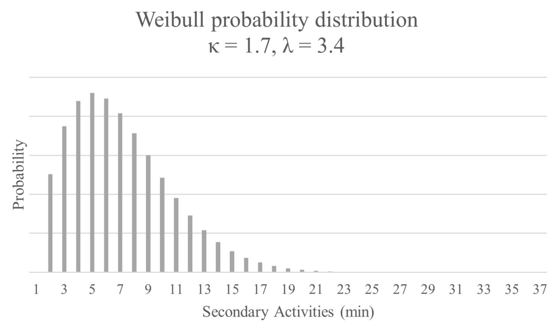



Figure 4.3: Weibull distribution used to model time of secondary activities within the on-site logistical process.

Table 4.9 shows the experimental design that tests the impact of the introduction of the secondary activities determined by the Weibull distribution. We choose Doetinchem as the experimental facility due to it having the most number of orders each year, meaning that at this location the measure causes to add the most extra processing/loading time. We run this experiment with and without the addition of this feature to see the impact on different maximum capacity levels.

| Experiment | Facility | Capacity factor Bulk | Capacity factor Bagged |
|---|---|---|---|
| F1 | Doetinchem | 0.4 | 0.8 |
| F2 | Doetinchem | 0.5 | 0.9 |
| F3 | Doetinchem | 0.6 | 1.0 |
| F4 | Doetinchem | 0.7 | 1.1 |
| F5 | Doetinchem | 0.8 | 1.2 |
| F6 | Doetinchem | 0.9 | 1.3 |
| F7 | Doetinchem | 1.0 | 1.4 |
| F8 | Doetinchem | 1.1 | 1.5 |
| F9 | Doetinchem | 1.2 | 1.6 |

Table 4.9: Experiments for Veendam to assess the impact of Weibull distributed secondary processes

### 4.3.5 Introduction of Arrival Timeslots

The use of scheduling entities to increase the performance of a system. Introducing scheduling in a system with random arrivals can result in reduced entity waiting time, server idle time, and server overtime costs. (Yidong Peng, 2014) Triferto indicated that they have plans to introduce timeslots where trucks can pick up their orders to better manage their loading operations. The goal of the following experiments is to study the potential of introducing timeslots and their effect on On-Time performance and capacity utilisation. Positive results can strengthen Triferto's business case of introducing these timeslots and can even lay a foundation for the method of implementation of this new system. Thus far, we assumed the random arrival of orders during the operating hours of Triferto's facilities.

Assigning a timeslot to each order is unrealistic for Triferto. Customer convenience is important and can lead to lost sales when jeopardised as stated by Triferto. However, all the random arrivals at the facilities are starting to become unmanageable. Some transporting partners give an estimated time of arrival when their transport plans are made, which helps with daily capacity management. Triferto has main transporting partners that might be willing to cooperate regarding pick-up agreements, which might be for a cost. Therefore testing the effect of scheduling a small portion of total daily orders is what this experiment does. Wing and Vanberkel (2021) provide multiple rules of thumb regarding scheduling in a system of random arrivals, of which the following are of relevance. The first of two relevant rules of thumb is scheduling at the start of the day allowing scheduled customers to be loaded while the backlog of the random arrivals is still small. This also lowers the chance of servers being idle at the start of the day. The next relevant rule is to schedule customers on time periods that correspond with moments when the random arrival of other customers is low. Since there is no quantitative data on customer arrival, we only incorporate the first rule of thumb in the simulation model due to arrivals being constant throughout the day. We experiment with this rule by having a small portion of orders arrive at the start of the day and keeping the total average daily orders the same. This means that the arrival rate of orders during the rest of the day is lower. The small portion of early arriving orders reflects the agreements made with transport partners that have close relations with Triferto. The first set of experiments in Table 4.10 study the effect of having different amounts of early scheduled orders on the baseline scenario shown in Table 4.5 in the case of Oss. We also analyse more realistic timeslot allocation between 0% to 15% of all orders in different capacity settings for the facility of Doetinchem. This should show the effectiveness of using timeslots in different maximum capacity scenarios.

| Experiment | Facility | Portion of early orders |
|---|---|---|
| G1 | Oss | 0 |
| G2 | Oss | 0.10 |
| G3 | Oss | 0.15 |
| G4 | Oss | 0.20 |
| G5 | Oss | 0.25 |
| G6 | Oss | 0.30 |
| G7 | Oss | 0.40 |
| G8 | Oss | 0.60 |
| G9 | Oss | 0.80 |

Table 4.10: Experiments for Breda that study the effect of different timeslot settings

## 4.4 Model Limitations

A simulation model is per definition a simplified and tuned-down version of reality. Also in the design of this model, there are choices that made the model simpler and manageable with the resources available. The following list sums up these limitations and the possible impact of them on the interpretation of the results.

- **Demand forecast.** Based on historical 2021 Triferto trends and amounts, plus a naive 2023 yearly forecast of Agrifirm. However, the model allows testing of other demand scenarios that can be generated by Triferto. Distribution of Agrifirm demand between bulk and bagged orders leans heavily to bagged orders, due to early season trends of Agrifirm orders in the first months of 2023.
- **Order arrivals and order size.** Demand is currently modelled as single orders that arrive randomly when a facility is open. In reality, orders are often pooled and picked up by a single truck. Increasing order size and decreasing order frequency without making other changes to the system likely result in the On-Time performance being more susceptible to stochasticity. Also, Triferto indicates that arrival intensity is certainly not the same throughout the day. They observe an arrival peak in the morning and early afternoon. However, Triferto does not have any data to support this, resulting in the simplification of assuming random arrival throughout the day.

## 4.5 Conclusion

This chapter answers the research question *"What should a simulation model that abstractly describes the reality regarding the impact of the throughput capacity on the loading process of Triferto's facilities to estimate On-Time delivery performance look like, and what information, parameters, and assumptions are required to make a valid simulation model?* in multiple steps. First, we describe the conceptual model by following a total of 5 steps. With a conceptual model, we have an idea of how this simulation should look to continue solving the On-Time problem statement. Then, an explanation is given of the model inputs and outputs, and the motivation behind them. The main output KPI of the model is the yearly On-Time order percentage. The target of this KPI is the same as the overall OTIF score: 97.5%. Next, a set of experiments are designed to run in the model. The first set of experiments set a baseline performance. The next two sets test the sensitivity of model basic inputs related to the logistical capacity and how they impact the On-Time performance of orders. Then, experiments are designed to test the effectiveness of having adaptive capacity adjustment as described in Section 3.1 by (Land et al., 1999). Since there is no available process data at Triferto, we enhance the model by designing experiments that add stochasticity that is based on qualitative information gained from Trifero and findings in the literature described in Section 3.2. Hereby we This is done by adding the option to make the loading speed normally distributed, and including secondary activities that are modelled by a Weibull distribution. Lastly, experiments are designed to assess the effectiveness of introducing timeslots to Triferto's systems, which they are already considering but have not started implementing. These experiments and their results are discussed in the next chapter to answer the next research question and reduce the uncertainty of future On-Time performance. During the modelling, various validation and verification techniques are used like bug fixing, testing extreme values, and tracing.

# Chapter 5

# Results

This chapter shows the results of the experiments defined in Chapter 4.3 and highlights interesting observations. Section 5.1 shows the results of the baseline scenario and the sensitivity analysis. Next, Section 5.2 shows the results of introducing extra stochasticity to the model and optimisation implementations. Lastly, 5.3 concludes the chapter.

## 5.1 Experimental Results

This section shows the results of all the experiments Section 4.3 describes, starting with the baseline performance, then the sensitivity analysis of total capacity and number of loading spots, and lastly the experiments that test the adaptive capacity adjustment methodology as described by Land et al. (1999). The focus is mostly on the On-Time delivery performance in each experiment, which is the main KPI of the model. At the end of this section, we answer the fourth research question about finding the model configuration that meets the On-Time target of 97.5% and uses the least amount of total capacity, for each facility.

### 5.1.1 Baseline performance

The first set of experiments determines the baseline On-Time delivery performance for all facilities. This baseline uses inputs that Triferto deems closest to reality at the moment of providing them and reflects the 2023 season, which includes Agrifirm orders. Figure 5.1 shows the results of the experiments described in Table 4.5 that results in the per product group On-Time performance in the baseline scenario. Table 5.1 shows the performance details of each facility.

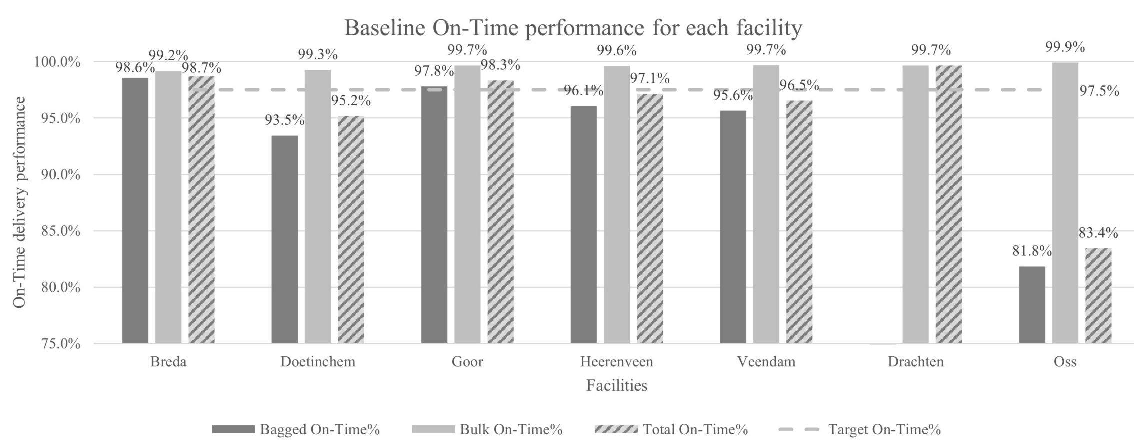



Figure 5.1: Baseline On-Time performance of all facilities

| Facility | Nr Bulk Late | Nr Bagged Late | Bulk On-Time% | Bagged On-Time% | Total On-Time% |
|---|---|---|---|---|---|
| Breda | 8.6 | 63.7 | 99.2% | 98.6% | 98.7% |
| Doetinchem | 24.3 | 516.6 | 99.3% | 93.5% | 95.2% |
| Goor | 6.5 | 109.5 | 99.7% | 97.8% | 98.3% |
| Heerenveen | 10.4 | 248.7 | 99.6% | 96.1% | 97.1% |
| Veendam | 5.6 | 285.9 | 99.7% | 95.6% | 96.5% |
| Drachten | 9.1 | - | 99.7% | - | 99.7% |
| Oss | 0.5 | 1229 | 99.9% | 81.8% | 83.4% |

Table 5.1: Overview of baseline performance for each facility

The results of the baseline experiments show that 95.0% of all orders are delivered On-Time. 99.6% of all bulk orders and 93.2% of all bagged orders are delivered On-Time. Three facilities, Breda, Goor and Drachten, are performing above the On-Time target of 97.5%. The other four facilities perform below the target, the worst being Oss, with only 83.4% of all orders being On-Time. This is the only facility with one loading spot for bagged products while other facilities have two. Doetinchem with an On-Time performance of 95.2% is the worst scoring facility with two bagged loading spots. When looking at individual product types, the results show that orders of the bulk categories are performing at a 99%+ On-Time rate. This indicates that there is a lot of over-capacity for this type. The bagged products are underperforming as only 3 out of 7 facilities that handle bagged products meet the 97.5% On-Time target.

Late deliveries happen throughout the year and depend on the available loading capacity and demand during that period. Figure 5.2 shows the daily demand, capacity and the number of late orders of the facility in Doetinchem. Doetinchems's base performance is a total On-Time delivery fraction of 95.2%, which is 2.3% below the performance target. Triferto indicated that during the high season, the chance of insufficient capacity is the highest. However, the results show half of the late orders (271, 50.1%) happen during the high season when demand is highest and capacity is at its maximum. When capacity is at its lowest, 31% in week 31 till the end of the year, 35% of all late orders occur. This means that not only during the season, but also during times with less demand a considerable amount of late orders occur. This implies that not only insufficient maximum capacity is a problem, but also capacity management via the capacity factor during the off-season. Additionally, there are periods where demand exceeds available capacity, resulting in inevitable late deliveries.

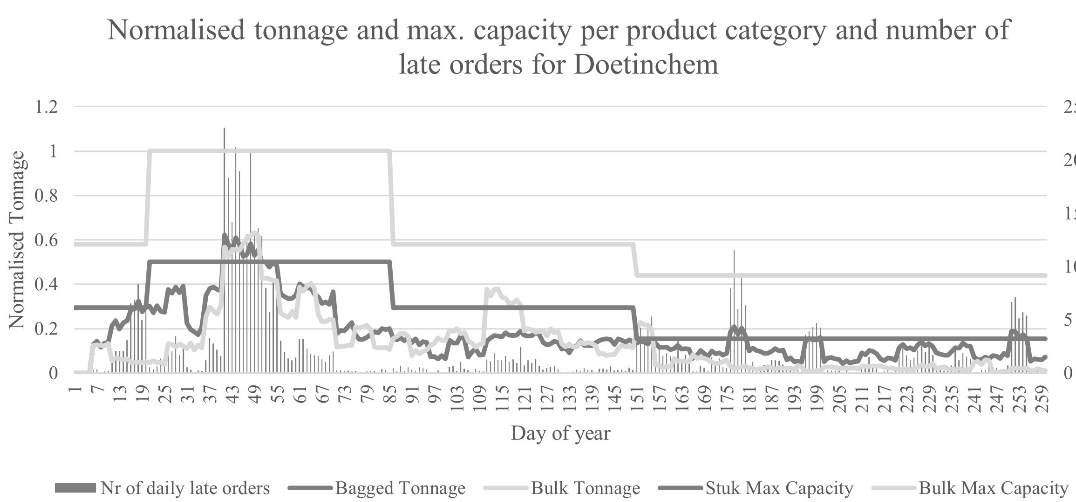



Figure 5.2: Daily demand, capacity and late orders of Doetinchem in baseline scenario

### 5.1.2 Sensitivity analysis

This section shows the results of the experiments defined in Section 4.3.2. Here, we test both the capacity factor and the number of loading spots to asses the systems' response. The main goal is to find a capacity setting that fulfils the On-Time target for each facility and to show the benefits adding more loading spots can bring to a facility.

**Capacity Factor.** The first set of experiments analyse the impact of varying the maximum available throughput capacity by in- or decreasing the loading speed of a single loading spot by multiplying with the capacity factor of the experiment. The experiments are done for each facility that Table 4.6 describes. Figure 5.3 shows the improvement trend of the On-Time performance of the bagged category while increasing the capacity factor. Each facility shows a similar improvement trend when increasing the capacity factor. Except for Oss, that facility shows a much slower improvement rate, which is likely due to there being one loading spot available instead of two. More on this specific case later in this section when we discuss the loading spots. Oss being much farther right in the graph indicates that doubling maximum capacity is required to meet the expected demand and fulfil the On-Time target.

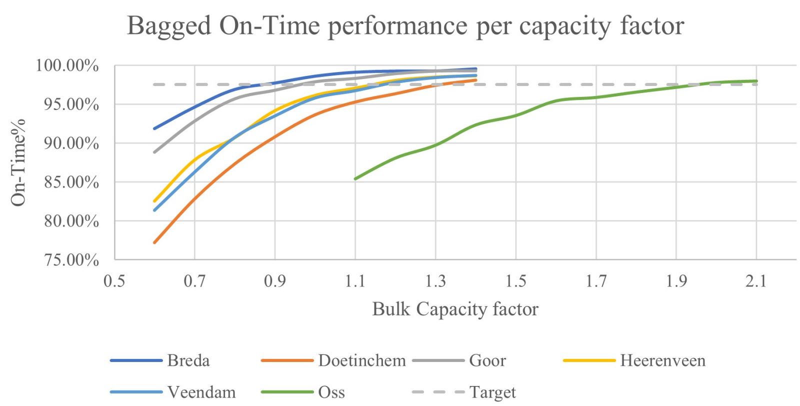



Figure 5.3: Daily demand, capacity and late orders of Doetinchem in baseline scenario

The results of all experiments give a setting for each one of the facilities, where the On-Time performance of each product group is higher than the 97.5% target. This setting is shown in Table 5.2 for each facility and is the main result of these experiments. For the bagged category, these points are the intersection with the target line and each facility in Figure 5.3. The table shows that generally, given the current demand settings, Triferto can do with systematically less bulk logistical capacity than initially thought. However, On-Time delivery of bagged orders seems to be the critical product group, which was expected by Triferto as Section 1.3.1 discusses.

| Facility | Bulk Cap. Factor | Bulk On-Time% | Bagged Cap. Factor | Bagged On-Time% |
|---|---|---|---|---|
| Breda | 0.7 | 97.9% | 0.9 | 97.3% |
| Doetinchem | 0.8 | 98.42% | 1.4 | 981% |
| Goor | 0.5 | 97.8% | 0.9 | 97.9% |
| Heerenveen | 0.6 | 98.50% | 1.2 | 98.1% |
| Veendam | 0.5 | 97.8% | 1.2 | 97.8% |
| Drachten | 0.5 | 97.8% | - | - |
| Oss | 0.2 | 98.3% | 2.0 | 97.8% |

Table 5.2: Loading process setup per facility to meet target

**Number of Loading Spots.** The last set of experiments within the sensitivity analysis tests the impact of adjusting the number of loading spots for bulk-type orders. The effect of varying the number of loading spots while keeping the total throughput capacity constant by decreasing the capacity factors is most interesting. Oss is the only facility that has one bagged loading spot, and performance is the worst in the baseline setting. Also, the capacity factor sensitivity analysis shows that a capacity factor of 2.0 is required to meet the target On-Time performance. Figure 5.4 shows the trend performance gain when adding new loading spots while keeping the same total available capacity. For example; doubling the number of loading spots means cutting the loading speeds of said spots in half, as shown in Table 4.7. This means when going from one to two loading spots, we cut the processing speed of a single loading spot in half. Table 5.3 shows the intersection with the target of 97.5% so we can determine the effectiveness regarding total available capacity and the possible savings. Increasing the number of loading spots and keeping the total capacity the same results in having a lower required capacity factor to meet the On-Time target of bagged products. The capacity savings seem to be close to linear and can save around 4% of the required maximum capacity when increasing the number of bagged loading spots in increments of one. However, practical inconveniences like insufficient space at a facility and/or acquisition of equipment to facilitate the increase might negatively impact the business case of increasing the number of loading spots.

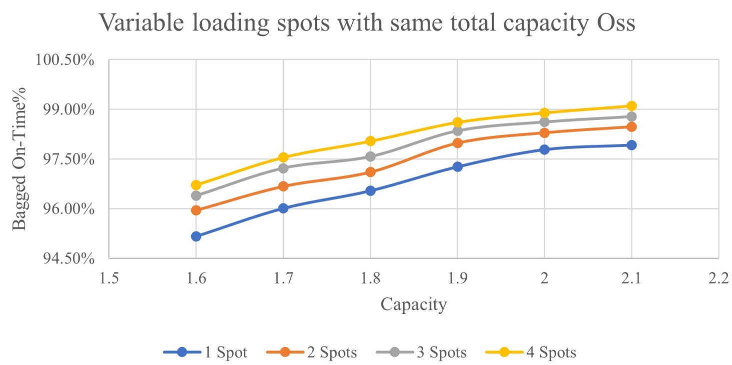



Figure 5.4: Number of loading spots with same total capacity Oss

| Metric | 1 Spot | 2 Spots | 3 Spots | 4 Spots |
|---|---|---|---|---|
| Bagged Cap. Factor | 1.94 | 1.85 | 1.775 | 1.7 |
| Baseline Diff. | - | 0.09 | 0.165 | 0.24 |
| Capacity Savings | - | 4.6% | 8.5% | 12.4% |

Table 5.3: Potential capacity saving when increasing the number of loading spots and keeping total capacity equal

## 5.2 Stochasticity and Optimisation Experiments Results

This section discusses the On-Time performance of the loading process when introducing normally distributed processing times as explained in Section 4.3.4.

### 5.2.1 Optimisation - Adaptive capacity adjustment

In this subsection, we discuss the results of the adaptive capacity adjustments discussed in Section 4.3.3 that show a resemblance with the method discussed by Land et al. (1999). Adaptive capacity adjustment is applied the next day when the loading process reaches a certain utilisation threshold specified within the experiment. Then, the next day the loading speed of all loading spots is multiplied with the increase factor. Table 5.4 shows the results of various settings of this optimisation policy. Figure 5.5 shows the effectiveness of adaptive capacity versus the normal trend when increasing capacity. The table and figure show that including an adaptive capacity policy results in a performance increase in the baseline scenario of Oss. Note that the performance of the baseline scenario is initially low (82.3%). The same experiments with the baseline scenario at Goor, which has a higher performance than the baseline for Oss, show no significant performance increase. Arguably, flexible capacity is a lot more expensive than normal capacity, which questions the true effectiveness of flexible capacity.

| Experiment | Bagged On-Time% | Effectiveness | Bagged Capacity |
|---|---|---|---|
| Oss Baseline | 82.3% | 0% | 100% |
| D1 | 85.6% | 3.4% | 105.9% |
| D2 | 85.3% | 3.0% | 105.6% |
| D3 | 85.1% | 2.9% | 105.2% |
| D4 | 87.5% | 5.3% | 111.3% |
| D5 | 86.8% | 4.5% | 110.5% |
| D6 | 87.4% | 5.1% | 109.2% |
| D7 | 88.8% | 6.5% | 116.1% |
| D8 | 88.7% | 6.4% | 114.4% |
| D9 | 87.9% | 5.7% | 112.8% |

Table 5.4: Results and baseline for Oss of various settings regarding adaptive capacity adjustments

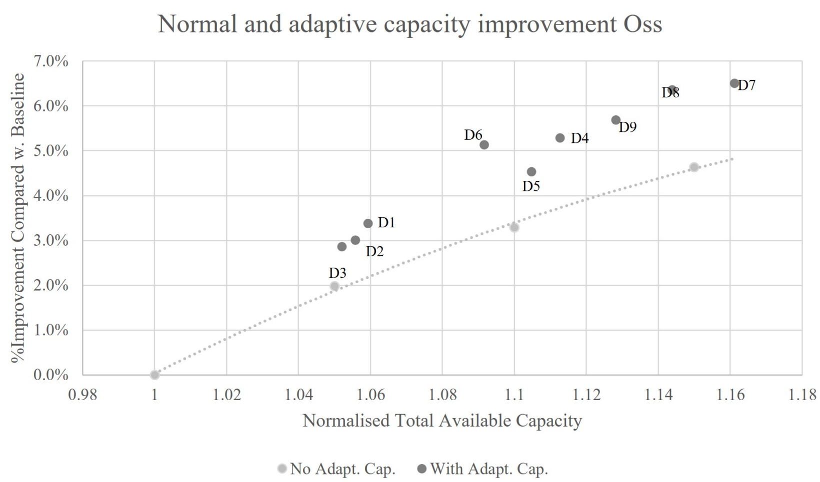


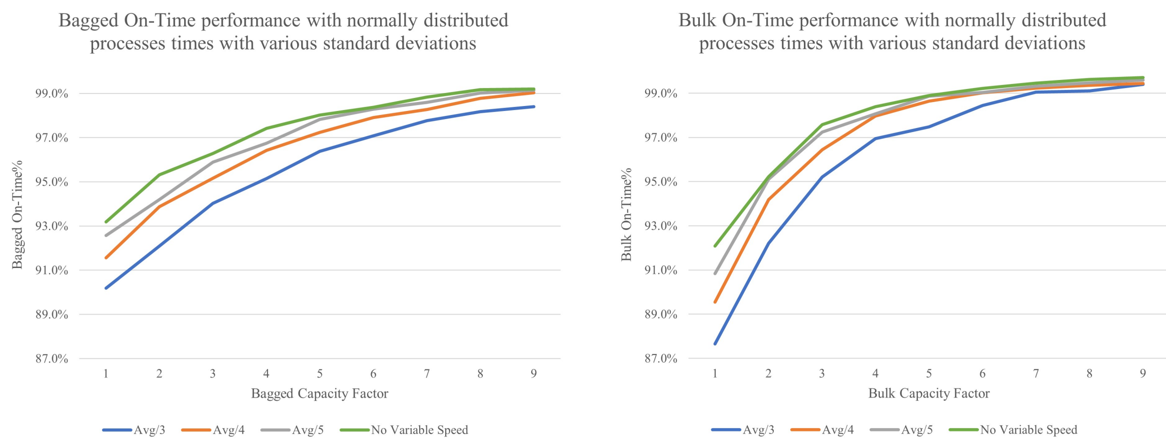

Figure 5.5: Effectiveness of adaptive capacity versus increasing total capacity

### 5.2.2 Stochasticity - Normalised order processing speeds

This section explains the results of some experiments regarding normally distributed loading speeds defined in Section 4.3.4. Figure 5.6 shows the performance of both product types in the case of Doetinchem. Results in Figure 4.2a show that, especially near the On-Time target of 97.5%, variability in loading speeds has minimal effect on the performance. However, when increasing the standard deviation of the loading speed enough effects can be seen. Figure 5.7 shows the distribution corresponding with the blue line in Figure 5.6. In reality, it is unlikely that the processing speed will vary this much as indicated by the blue line. Therefore we see that normally distributed loading speeds do not have much impact on delivery performance when managing realistic variability.

### 5.2.3 Stochasticity - Weibull distributed Secondary Activities

This section shows the results of the experiments explained in the second part of Section 4.3.4. In prior experiments, secondary activities like truck check-in and the use of a weighing bridge were not specifically included




(a) Bulk (b) Bagged

Figure 5.6: Impact normalised process speeds on On-Time performance Doetinchem

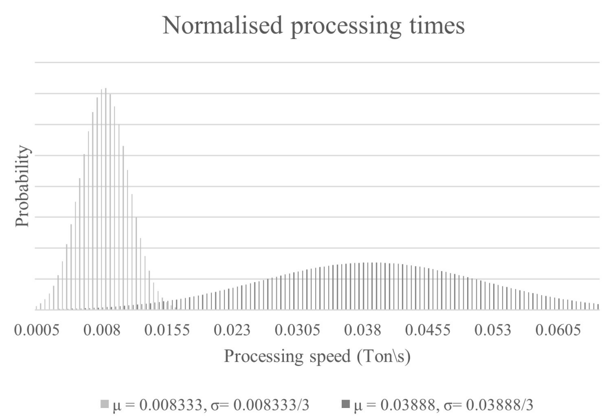



Figure 5.7: Process speed distributions in most extreme experiment

within the model. Here we study the effects of adding 3 minutes per order and adding time drawn from the Weibull distribution with a shape ($\kappa$) of 1.7 and size ($\lambda$) of 3.4. The average extra time of 3 minutes is qualitatively based on the expert opinion of the facility manager at Doetinchem. We assume this average is similar at the other facilities. Figure 5.8 shows the results for the facility with the most yearly number of orders, Doetinchem. The additional process time per order does have an effect on the On-Time performance. The impact is so large that a capacity increase of 18% is required to compensate for the performance loss (capacity factor 1.4 to 1.7). The figure also shows that the stochasticity induced by the Weibull distribution does not induce additional harm to the On-Time performance compared with the constant addition of 3 minutes. This implies that the system is sensitive to more process time, but not to the variability of the added process time.

### 5.2.4 Optimisation - Introduction of Timeslots

Triferto considers introducing timeslots to their customers when they can pick up their orders. This is to better manage capacity and be less dependent on the random arrival of trucks. In this subsection, we analyse the results of the experiments described in Section 4.3.5 and Table 4.10. Figure 5.9 shows the On-Time performance increase when increasing the number of orders that are available to be processed at the start of each day. In the case of Oss, bagged products cause the most late orders which is more than 99.5% of all late orders. In this experiment, we see the performance of a bagged capacity factor that is close to the target performance (capacity factor 1.8) and one that is structurally lower (capacity factor 1.5). Both lines follow a similar trend. However, we see

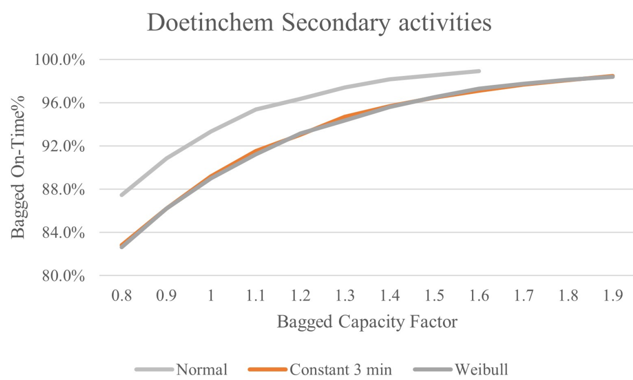



Figure 5.8: Secondary activities inclusion at Doetinchem

that with worse initial performance, introducing timeslots yields better improvement than when having a higher base capacity. Figure 5.10 shows a similar trend in the case of Doetinchem. Here we see that the effectiveness of increasing the number of orders allocated to timeslots quickly decreases when increasing the percentage of orders being allocated to timeslots. Results show that around the On-Time target performance, about 10% in maximum capacity can be saved when only 5% of daily orders are allocated to the opening time in the case of Doetinchem. Further performing gains by increasing the number of early orders is minimal at this level of On-Time performance.

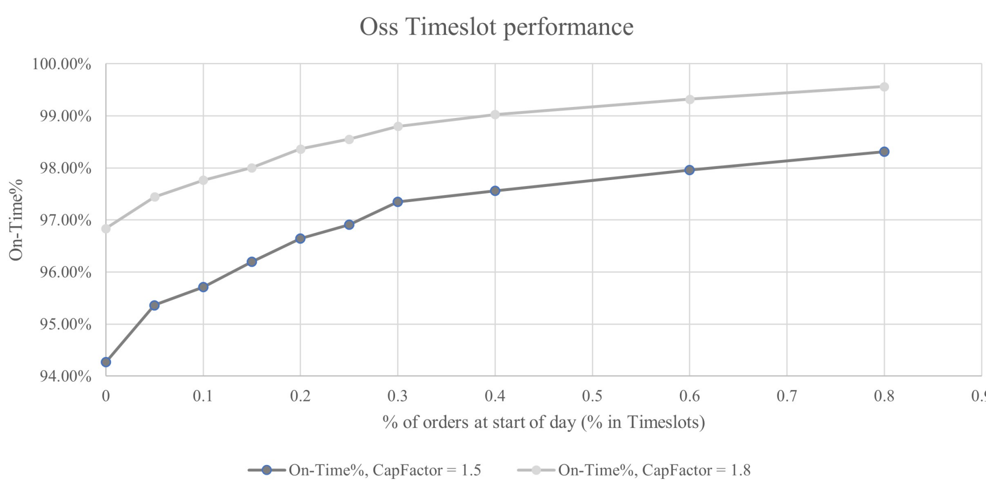



Figure 5.9: Oss On-Time performance with different Timeslot settings

Additionally in the case of Oss, we see that when almost all orders (80%) are present at the beginning of the day, there still seems to be an upper bound for the On-Time performance. This is due to structural insufficient performance during certain periods of the year. Figure 5.11 shows the yearly demand and maximum daily throughput together with the average number of late orders when having 60% daily orders available at the start of the day (considered Timeslots). This occurrence is most notable around day 150, where the daily tonnages exceed the daily available capacity. This is also notable around the 45 and 120-day mark. This means that no time schedule can prevent late orders in this maximum capacity case.

Now to conclude regarding the introduction of timeslots. Having timeslots that enable some customers to be available at the start of the day leads to better On-Time performance. This is due to there being less capacity utilisation loss during the start of the day, which allows the randomly arriving orders to come in and create a backlog.

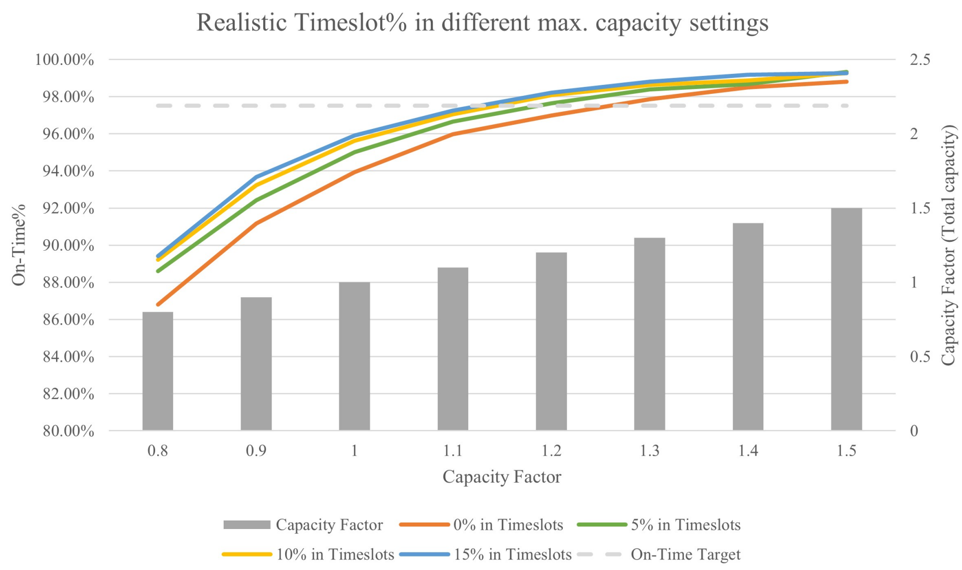



Figure 5.10: Doetinchem Timeslot% performance in different max. capacity settings

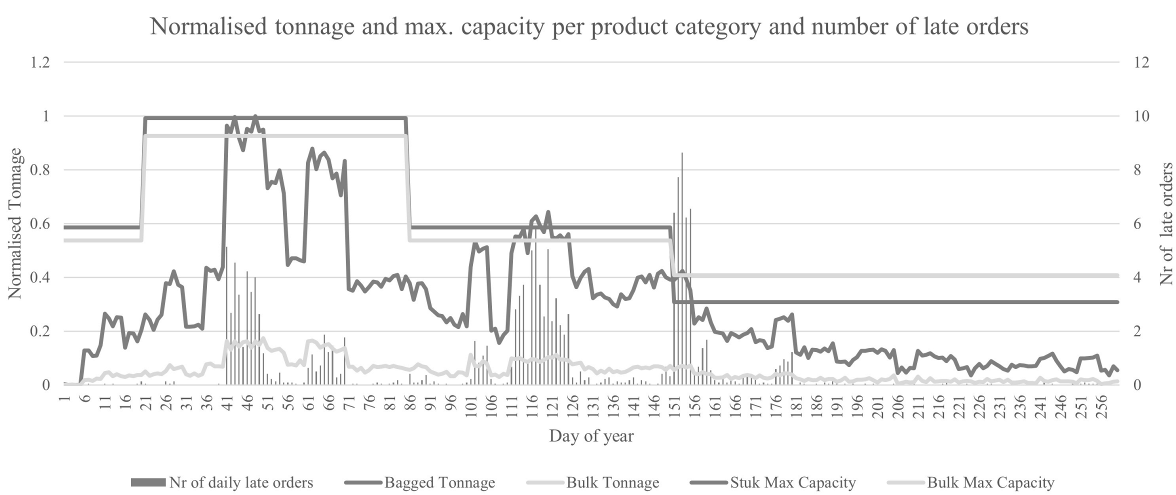



Figure 5.11: Daily tonnage, capacity and number of late orders in a year, Oss

Only a small portion of 5 to 10% of customers allocated to timeslots give improved performance. Increasing this percentage only gives marginal improvements and is not considered effective. Assigning all daily customers to a timeslot, which results in optimal capacity utilisation does not always solve the On-Time performance problem due to the possibility of demand exceeding total capacity during certain periods.

## 5.3 Conclusion

In this chapter we answer the fourth research question; *What model configuration is required to meet the On-Time target of at least 97.5% while minimising maximum logistical throughput capacity for the different facilities Triferto operates?* First, we find the baseline performance for each facility without modifying the characteristics of orders and facilities. 4 out of 7 facilities do not meet the 97.5% On-Time target that are Doetinchem, Heerenveen, Veendam, and Oss. The bagged product type is the most problematic of the two, which was expected and was indicated by Triferto. Then, a sensitivity analysis that tests the available capacity and the number of loading spots, results in an setting where each facility and product group reaches target performance. The main observation here is that bulk capacity can drastically be reduced, while bagged capacity needs to be increased. Specifically, Oss requires a doubling of bagged capacity to meet the target. Additionally, we test the system's reaction to stochasticity in both process speeds and the addition of secondary activities. The system is resilient for stochasticity in loading speed and additional loading time, however, structurally adding process time due to secondary activities does have a negative impact on performance. This requires a further capacity increase to meet the target. Lastly, two system optimisation methods are tested, adaptive capacity management and the introduction of timeslots. Using adaptive capacity does yield a performance increase, which is more efficient than simply increasing the maximum capacity. Arguably, adaptive capacity is more expensive than regular capacity, so the business case should be carefully considered. Introducing timeslots to the system results in performance gains (increase from 88 to 90%) when only scheduling 5% of orders at the start of the day. Scheduling more customers has minimal effect. However, implementing timeslot usage when performance is already near the target is less effective. In the case of Doetinchem, a 5% timeslot allocation increases performance go from 97.3 to 97.7%, which translates to a potential capacity saveing of 4 to 7%.

# Chapter 6

# Conclusions and Reccomendations

This last chapter concludes this research in Section 6.1 by revisiting the research objectives and questions and listing the main conclusions. Next, recommendations toward Triferto regarding the results and conclusions are explained in Section 6.2. Section 6.3 explains two cases that are larger and transcend the scope of this research. Lastly, Section 6.4 explains the practical and theoretical contribution of this research.

## 6.1 Conclusions

Triferto entered into cooperation with Agrifirm and will from 2023 handle the fertiliser branch of Agrifirm. This includes the doubling of demand organisation-wide and new contractual obligations for both parties. Drastic measures on multiple fronts are required to make this collaboration a success. This research focuses on one of these fronts; the delivery performance of orders according to the On-Time, In-Full philosophy. The target set by Agrifirm and Triferto is that 97.5% of all orders in a year should be delivered On-Time and In-Full for both bulk and bagged orders. Triferto will be financially penalised when this target is not met. Triferto is uncertain of its capability to meet this target. Historical data analysis gives insight into the historical and expected In-Full performance. Next, a simulation model is built to assess different scenarios and settings within the loading process to assess the expected On-Time performance. The following list explains the main conclusions of this research that reflect the topics in the 5 research questions and research objectives, following their order.

- **Immesureable historical On-Time performance.** Here we make a distinction between On-Time and In-Full performance. An order is delivered On-Time when it is shipped on the target date. Prior to the collaboration, no On-Time performance was measured. Due to this, we could not determine the historical On-Time performance. Therefore we built a simulation model to estimate future On-Time performance that other items explain.

- **89% upperbound (historical) OTIF performance.** 14% of all bulk orders of 2021 are not delivered In-Full. A bulk order has a 200kg error margin to be delivered In-Full. A bagged order is delivered In-Full when the ordered amount exactly matches the delivered amount since the product units are innumerable. Here, we assume all bagged orders are delivered In-Full. Every facility does not meet the 97.5% In-Full target within the bulk category. Breda performs worst with 51%, and Heerenveen performs best with 95% In-Full performance for all its bulk orders. Additionally, the upperbound figure also assumes every order is delivered On-Time. Should this trend continue into 2023, Triferto is unlikely to meet the OTIF target.

- **Throughput capacity impacts delivery performance.** Agrifirm and Triferto introduce new delivery performance targets to guarantee their customers a certain quality standard. Reviewing literature shows that (throughput) capacity, and its flexibility, do have an impact on response to customer demand, lead times and deliverability. OTIF is defined within the literature as the perfect order and relates to customer satisfaction, which is in line with the common goal of both Triferto and Agrifirm.

- **Simulation fits problem context.** Literature showed that simulation is common and useful within transportation and logistic system modelling. Discrete event simulation is the type used within this research.

Following a conceptual model design, a simulation model is made that can assess On-Time delivery performance of all in-scope facilities during a full year per product category. The most important inputs for this model are demand data, order size distributions, loading speeds, number of loading spots and seasonal capacity management.

- **95.0% On-Time performance in baseline scenario.** 99.6% of all bulk orders and 93.2% of all bagged orders are delivered On-Time. The baseline uses inputs that Triferto thinks are closest to reality. 4 out of 7 facilities do not meet the On-Time target of 97.5%. Figure 5.1 shows On-Time performance for each product category. Results of the simulation show that Oss performs worst with only 83% orders delivered In-Full. Breda performs best with both categories performing above 98%. 4 out of 6 facilities do not meet the bagged On-Time target. All facilities amply meet On-Time performance (>99%) for their bulk orders. Late orders occur both during the season when capacity is at its maximum and during the rest of the year when the capacity is throttled to lower levels. In the case of Doetinchem, 50% of late orders occur during the season.

- **Triferto not meeting OTIF target for 2023.** Combining historical data analysis and results of the simulation model in the baseline scenario, we conclude that Triferto is expected to deliver 91.1% of their orders OTIF in 2023. This is 6.4% short of the 97.5% OTIF target. This means that Triferto will not receive a bonus for 2023 and will be financially penalised in upcoming years if no action is taken. Table 6.1 shows an overview of the combined results. Only percentages are shown due to it being sensitive information. Despite Triferto indicating that the bagged category will likely be the culprit of underperformance, results show that the bulk category has a lower OTIF performance (85.6%) than the bagged category (93.2%).

| Metric | Bulk | Bagged | Combined |
|---|---|---|---|
| On-Time% | 99.6% | 93.2% | 95.0% |
| In-Full% | 86.1% | 100.0% | 96.1% |
| **OTIF%** | **85.6%** | **93.2%** | **91.1%** |

Table 6.1: Expected OTIF performance Triferto 2023

- **Large bagged capacity increase required to meet On-Time target.** The results of the sensitivity analysis show what capacity adjustments are required to meet the On-Time target of 97.5% in Table 5.2. In the experiment, capacity is managed by a capacity factor. This factor is multiplied by the loading speed of a loading spot for both product categories. Goor and Breda can manage to meet the bagged target with 90% capacity. Oss needs 200% capacity to meet the target. All facilities can manage bulk orders with structural a capacity decrease. Increasing the number of loading spots for the bagged category while keeping total capacity the same via decreasing capacity factors results in better performance. This translates to potential capacity savings of around 4% per additional loading spot, up to a total of four bagged spots.

- **Introducing stochasticity to loading speed and secondary activities has minimal effect on On-Time performance.** We test the effect of stochasticity in the loading speed and secondary activities like check-in and truck weighing, in addition to already existing stochasticity in the demand generation (order arrival and size). Results show minimal impact on both product types when making the loading speed normally distributed. When increasing the standard deviation to abnormal levels, we observe a performance decrease. Introducing secondary activities to the model via a Weibull distribution with an expected value of 3 minutes. does negatively impact the On-Time performance for both product types. However, no difference is observed in comparison to constantly adding 3 minutes of loading time. Therefore we conclude that the system is sensitive to additional processing time instead of the stochasticity of this extra time.

- **Adaptive capacity adjustment has a negligible effect on performance** No significant performance increase is observed with the introduction of this optimisation measure when performance is nearing the target. Note that it does show a considerable performance increase between 2.9% and 6.5% when the scenario setting has lower performance in the case of Oss.

- **Timeslots are quick-win of 10% in capacity saving.** Results show that allocating 5% or 10% of orders to timeslots shows an On-Time performance increase of 0.5% or 0.8% when nearing the target in the case of Doetinchem. The performance gain of having 5% of orders in timeslots translates to a similar improvement when increasing the total capacity by 4 to 7%. For the case of this research, allocating these orders at the start of the day is the most effective due to having less idle time and being less dependent on arriving orders. Allocating more orders to timeslots keeps improving performance but becomes less effective.

## 6.2 Reccomendations

The following points form a list of recommendations to Triferto based on the historical data analysis, process analysis and results.

- **Improve data collection.** A recurring theme within this research project was data availability. Many assumptions are made in the making of this thesis. While the most important ones are validated with key stakeholders, having quantitative data can contribute to better decision-making in similar future undertakings like this research or internal projects. We recommend increasing the data collection that gives more insight into processes on the facilities like the one discussed in the research, but also other processes like production. Also, the historical order data quality can be improved. Multiple anomalies and missing information were found during this research.

- **Consider baseline OTIF results.** The results regarding the expected 2023 OTIF performance should function as a warning for them not meeting the target within the agreement. Triferto did make improvements to their organisation to meet the new contractual agreements, some of which might not be considered in this research that can improve OTIF performance. However, this research considers at least two fundamental data sources that are the historical order data and capacity calculations. The historical data analysis exposes the previously unmonitored In-Full performance of bulk orders as insufficient and uses the loading capacity calculations in determining expected the 2023 On-Time performance. We recommend validating the assumptions made, especially regarding demand and capacity calculations, within the thesis with experts and interpreting the results accordingly.

- **Adaptive capacity.** Using an adaptive capacity similar to the one implemented in this research can be clumsy and expensive. This means that extra equipment and staff should be available to increase capacity. Implementing this efficiently could be difficult or impossible. Also, given the underwhelming results regarding On-Time performance increase, we recommend not pursuing this concept further unless additional information shows otherwise.

- **Timeslots.** In contrast to adaptive capacity adjustment, the introduction of timeslots does show promising results. The way it is studied in this thesis is in line with leads Triferto declared feasible. The research shows that a small amount of customers results in significant performance gains and/or capacity reductions. We recommend Triferto add the results regarding timeslots to their business case of introducing timeslots and engage with their main transporting partners to see if they are willing to cooperate since only a small amount of orders in timeslots can mean a lot.

## 6.3 Future work

This section explains to subjects of future work that can be considered by Triferto. Most recommendations highlight future work, but the two mentioned in this section are of a larger nature and transcend the scope of this research.

- **Combined Agrifirm and Triferto forecast.** A big part of the determination of the On-Time performance is the forecast for 2023. The demand data within this research is based on historical Trifero order data for 2021 and a naïve Agrifirm forecast for 2023. Additionally, the distribution of Agrifirm amongst facilities is based on a small amount of recent data. Additionally, in-depth analysis of the seasonal trends within the fertiliser industry could prove useful in determining forecasts not only on yearly numbers but also in predicting load on various other systems used within Triferto other than the one of this thesis like purchasing, production, storage, and loading.

- **Contious improvement within Triferto/Agrifirm collaboration.** This point of future work builds on the first point made in Section 6.2 where the recommendations are made. The first year of the collaboration is considered a try-out year and can highlight pain points for both parties that obstruct a successful collaboration. The findings of this try-out year can be a foundation for future research on how these can be resolved. Likely, some of these points relate to or can be solved with new data collection that has interfaces with data used in this research or completely new ones.

## 6.4 Contribution

This section discusses the contribution to both practice and theory.

### 6.4.1 Contribution to Practice

This research contributes to practice in multiple ways. This research reduces the uncertainty of Triferto's current and historical In-Full performances. The quantitative results challenge the expert opinions on which the feasibility of the 200kg error margin is made. Next, this research documents previously undocumented qualitative information from different experts and combines them into an overview of processes relevant to this research. Examples are the factors determining the throughput capacity, process maps, improving data quality, etc. This research also serves as a warning to be weary of their delivery performance during the collaboration and highlights the risk of suffering financial penalties incurred by not meeting OTIF targets. Lastly, this research studies the potential of two optimisation implementations (adaptive capacity adjustment and timeslots) supported by the literature. This contributes to a business case Triferto is working on.

### 6.4.2 Contribution to Theory

Chapter 3 studies literature that considers logistical/transport systems regarding bulk materials, like fertiliser. Most of these studies consider systems that have a large size like ports or mines. Also, these studies consider constant loading amounts that are often full truck loads. Lastly, performance in these studies is often measured by utilisation levels of various pieces of equipment. In this research, we study a similar process that is an internal process that considers the loading of bulk products. There are some unique aspects to this research that add to the scientific body that is (i) considering a smaller magnitude of facility, (ii) introducing varying loading/order sizes, (iii) introducing heavy seasonally and assessing performance over a whole year and (iv) being delivery performance focussed instead of having a more economic/efficient focus. Lastly, this study adds to the many studies that deem computer simulation a fit modelling technique to model transport/logistical systems.

# Bibliography


Agrifirm. Agrifirm: Passie voor landbouw, 2022. URL `https://www.agrifirm.nl/over-ons/agrifirm-in-nederland/`.

J. Banks. Introduction to Simulation. *Winter Simulation Conference 1999*, 1997.

E. Bonabeau. Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences of the United States of America, Vol. 99, No. 10*, 2002.

J. R. Bradley and B. C. Arntzen. The Simultaneous Planning of Production, Capacity, and Inventory in Seasonal Demand Environments. 1999.

N. K. P. Branislav Dragovic, Ernestos Tzannatos et al. Simulation modelling in ports and container terminals: literature overview and analysis by research field, application area and tool. *Flexible Services and Manufacturing Journal, 29(1)*, 2016.

CAPE Groep. Over cape, 2022. URL `https://www.capegroep.nl/over-cape/`.

O. Chagas et al. Production and Distribution Optimization of Bio-Based Fertilizers. *CIRRELT*, 2020.

M. Christopher. *Logistics and Supply Chain Management: Strategies for Reducing Cost and Improving Service (Second Edition).* Pitman Publishing, 1992.

M. Christopher. *Logistics & supply chain management.* Pearson Uk, 2016.

R. David and P. I. Collier. The simulation of a fork-lift truck and crane transfer operation. *Maritime Policy & Management, 6(2)*, 1979.

B. González, Hidalgo. Understanding individual human mobility patterns. *Nature, 453*, 2008.

R. E. M. Gunasekarana, C. Patelb. A framework for supply chain performance measurement. *Int. J. Production Economics 87*, 2004.

J. P. Kleijnen. Verification and validation of simulation models. *European Journal of Operational Research 82(1)*, 1995.

S. Laarova-Molnar and L. Xueping. Deriving simulation models from data: Steps of simulation studies revisited. *Winter Simulation Conference 2019*, 2019.

M. J. Land et al. The Simultaneous Planning of Production, Capacity, and Inventory in Seasonal Demand Environments. 1999.

A. M. Law. *Simulation Modeling and Analysis*. Mc Graw Hill Education, 2015.

L. R. Leitea et al. Supply chain resilience and key performance indicators: a systematic literature review. *Production 28*, 2018.

Y. Lizotte and E. Bonates. Truck and shovel dispatching rules assessment using simulation. *Mining Science and technology 5*, 1987.

B. Maskell. *Performance Measurement for World Class Manufacturing.* Productivity Press, Inc., 1991.

M. Neagoe et al. Using discrete-event simulation to compare congestion management initiatives at a port terminal. *Simulation Modelling Practice and Theory 112*, 2021.

M. Nedvědová et al. A Simulation Study of Depot with Multiple Temperature Modes: Maximum Flow Estimation. *IEEE 15th International Scientific Conference on Informatics)*, 2019.

J. Nutaro. Discrete event simulation of continuous systems. *Oak Ridge National Laboratory*, 2007.

D. K. Pace. Modeling and Simulation Verification and Validation Challenges. *Johns Hopkins APL Technical Digest, Volume 25, Number 2*, 2004.

Y. C. . H.-s. P. Park et al. Optimization of truck-loader haulage systems in an underground mine using simulation methods. *Geosystem Engineering*, 2016.

S. Robinson. Conceptual modelling for simulation Part II: a framework for conceptual modelling. *Journal of the Operational Research Society (2008) 59, 291 -304*, 2008.

S. Robinson. A tutorial on conceptual modeling for simulation. *2015 Winter Simulation Conference*, 2015.

A. Rockwell. Arena simulation software, 2023. URL `https://www.rockwellautomation.com/en-us/products/software/arena-simulation.html`.

C. Runciman, Vagenas et al. Simulation of Haulage Truck Loading Techniques in an Underground Mine Using WITNESS. *SIMULATION*, 1997.

R. G. Sargent. Verification and Validation of Simulation Models. *2010 Winter Simulation Conference*, 2010.

A. F. Seila. Introduction to Simulation. *Winter Simulation Conference 1995*, page 9, 1995.

N. Slack et al. *Operations Management, 5th edition*. Pitman Publishing, 2003.

Triferto. Over ons, 2022. URL `https://www.triferto.eu/nl/home#step-5`.

B. Wahyudi and I. N. Pujawan. Simulation of In Bag Fertilizer Loading Process In Port of Petrokimia Gresik to Increase Loading Rate. *International Conference on Management of Technology, Innovation, and Project (MOTIP)*, 2020.

J. Wing and P. Vanberkel. Simulation optimisation for mixing scheduled and walk-in patients. *Health Systems (Blasingstoke), 11(4)*, 2021.

J. S. Yidong Peng, Xiuli Qu. A hybrid simulation and genetic algorithm approach to determine the optimal scheduling templates for open access clinics admitting walk-in patients. *Computers & Industrial Engineering, Volume 72*, 2014.

# Appendix A

# Simulation Steps

In this section, we describe the steps in a simulation study which we use to answer the main research question. Figure A.1 (Law, 2015) shows the steps of a typical simulation study which are considered the traditional steps. Here, the conceptual model is developed on the basis of mostly expert knowledge. Based on this conceptual model relevant data is gathered which is then used for the building of the model itself. Other sources that discuss the process of building a simulation model like Seila (1995) and Banks (1997) follow similar methods. The literature also contains other simulation study approaches which are modernised. Laarova-Molnar and Xueping (2019) revisit these traditional steps to take advantage of and utilise the ongoing progression and development of data availability within companies. This new approach is data-based and uses for example process mining algorithms to extract workflows from event logs and pulls the data collection phase of the traditional method to the front of the simulation study. Triferto is a small-to-medium enterprise and does not gather lots of data (continuously) which relevant to this research and is not as data-driven yet as compared to more sophisticated and bigger companies in other sectors. The desire to become more data-driven, largely due to the collaboration with Agrifirm, is there and is on the agenda of Triferto for the upcoming years. Therefore we decided to use the conventional method to execute a simulation study for this research. Below are the steps of this traditional approach.

**Step 1.** The first step of a simulation formulates the problem and describes the global planning of the simulation study. Now the overall objective of the research and specific questions of what the study should answer are set. Additionally, the scope of the research is defined and the subject-matter experts/stakeholders are inventoried. Chapter 1 is about the first step of this research.

**Step 2.** The second step is about data collection and designing a conceptual simulation model. Information collection about the operating procedures is supported by data collection for the model parameters and input probability distributions. Also, one important deliverable of this step is setting up an assumptions document, which contains the written assumptions used within the study. Start with a simple model build upon it a check validity regularly. Also, interaction with key stakeholders is important in this step of the simulation study.

**Step 3.** In the last step before programming we validate the list of assumptions with the key stakeholders. If this document needs adjustment, going one step backwards is required and collecting the data required to make the assumptions complete or correct. It is important to consider 2 and 3 thoroughly to prevent major reprogramming at a later stage.

**Step 4.** In this step we program the simulation model. Normally, using a programming language like C or Java results in low purchasing costs because of program availability, but high project costs due to many development hours. Simulation programs on the other hand can have high purchasing costs due to licensing but save project costs due to convenient programming. Also, debugging of the simulation model is part of this step.

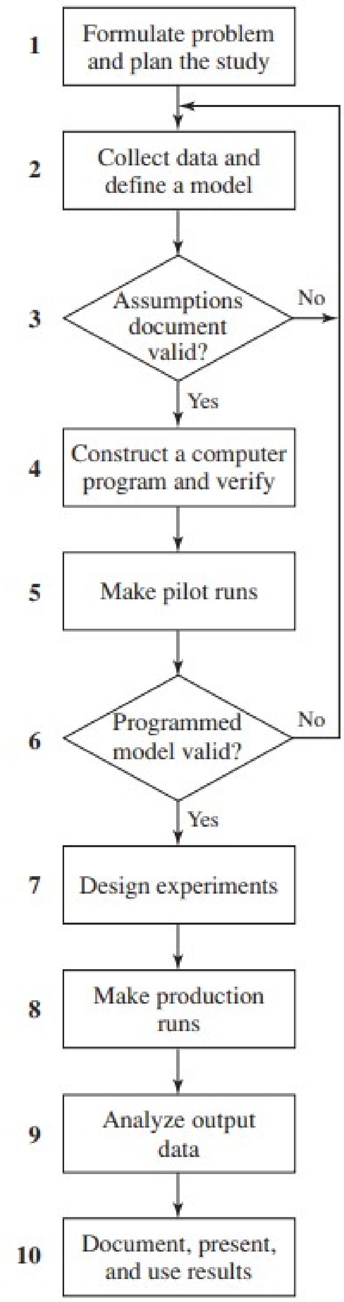



Figure A.1: Steps in a simulation study. (Law, 2015)

**Step 5 & 6.** In step 5 we design pilot runs based upon the current system used in step 6, which is the validation of the simulation model. Validating a simulation model is done by comparing the performance parameters of the simulation model with the existing system. Also, key stakeholders should review the model and its results for correctness. Lastly, a sensitivity analysis shows what model factors have a significant impact on the results. These factors should be modelled carefully. When the simulation model turns out not to be valid, new data needs to be collected and added to further improve the model and make it valid.

**Step 7 & 8.** In step 7 the configuration(s) of interest are defined. These often alternations of the current system and reflect the research objectives and questions of the simulation study. These are the experiments. The experiments have a certain length, and warm-up period if required and use different random numbers in each simulation run. The amount of runs for each specific experiment determines the confidence interval of the results. In step 8 we execute the experiments designed in step 7.

**Step 9 & 10.** Step 9 analyses the output data of the experiments which results from running the experiments in the simulation model. Important is determining the absolute performance of certain system configurations based on the different experiments. Also, the comparison between these configurations belongs in step 9. In step 10 use the results of the experiments and combine them to present the findings of the simulation study. Also, documenting the project is important for example future projects or decision-making for the actual system. The modelling and validation process of the simulation study is also discussed in step 10.

# Appendix B

# Conceptual Model

## B.1 Modelling and general project objectives

***Organisational Aim***

The overall aim for Triferto is to meet delivery performance targets set between Triferto and Agrifirm while making optimal use of their resources related to logistical throughput capacity for each facility which is in scope for this research.

***Modelling Objectives***

- Minimize overtime which in reality resembles orders that negatively impact on-time delivery performance. (minimum OTIF target of 97.5%)
- Minimizing logistical throughput capacity in different scenarios for each in-scope facility while still considering the first objective.
- Analysing the impact of capacity/demand adjustments on the amount of overtime and order waiting time.
- If available project time constraints allow: simulating potential logistical throughput capacity reduction by adding time slots for (part of all the) orders.

***General project objectives***

- *Time-scale*: Part of master-graduation thesis - 8 weeks.
- *Flexibility*: Decent flexibility is required since we simulate multiple facilities with different parameters and demand properties. Additionally, the bonus model objective requires extra flexibility because extra potential functionality to model.
- *Run-speed*: Moderately fast, since available computational power for this project is the power of a university-grade laptop. Additionally, many experiments were required since simulating each working day of the year for a total of 7 facilities and doing rigorous sensitivity testing.
- *Visual display*: Simple 2D animation. (Model is required for performing experiments, obtaining results and exporting them for further analysis. Therefore advanced graphical details are not required. However, a clear overview of the processes within the simulation can help verify and validate the model with the stakeholders since limited simulation experience is present)
- *Ease-of-use*: Simple features should suffice since the model is only used by the modeller. However, adjusting facility-specific parameters should be easy to adapt to input from stakeholders since the original parameters are primitive.
- *Model/component reuse*: Model needs to be used for likely several iterations during the project, but is likely unused after this project since corporate licensing is too expensive.

## B.2 Model Outputs/Responses

***Outputs (to determine achievement of objectives)***

- Daily logistical throughput capacity utilization
- Daily percentage of orders that experienced waiting time
- Daily total & average order waiting time

***Outputs (to determine reasons for failure to meet objectives)***

- Daily amount of overtime
- Daily number of orders fulfilled after closing time

## B.3 Experimental factors

***Experimental factors***

- Order frequency
- Order size
- Ratio bulk/bagged orders
- Maximum available logistical throughput capacity
- Percentage of maximum available logistical throughput throughout the year
- Facility

## B.4 Model Scope

| ***Component*** | ***Include/ Exclude*** | ***Justification*** |
|---|---|---|
| *Entities* | | |
| Orders | Include | Main entity that moves through the systems and resembles demand. |
| Trucks (customers) | Exclude | Significant difference between facilities, and no data availability about truck movements on the premises. Therefore generally considered in total available capacity. |
| *Activities* | | |
| Check-in at Facility Manager | Exclude | Not a bottleneck and has minimal/no impact on logistical throughput capacity. |
| Freight movements within facility grounds | Exclude | Does affect the logistical throughput capacity due to space limitations of facilities, but no data available and therefore generalised in total available logistical throughput capacity. |
| Loading process of order | Include | Main bottleneck of logistical throughput. |
| Check-out at Facility Manager | Exclude | See 'Check-in at Facility Manager'. |
| *Queues* | | |
| Check-in at Facility Manager | Exclude | See 'Check-in at Facility Manager'. |
| Loading spot/dock | Include | Gives waiting time indication for orders and is linked to daily overtime which resembles late orders. |
| Check-out at Facility Manager | Exclude | See 'Check-in at Facility Manager'. |
| *Resources* | | |
| Equipment | Include | Available equipment varies during the year due to other (seasonal) activities like unloading products from ships and production. |
| Employees | Exclude | Out of scope for research due limited data & additional complexity. |

## B.5 Model Level of Detail

| ***Component & Detail*** | ***Include/ Exclude*** | ***Justification*** |
|---|---|---|
| ***Entities*** | | |
| ***Bagged & Bulk orders*** | | |
| *Quantity*: 1, which is fertiliser | Include | Experimental factor and affects each Output/Response |
| *Arrival pattern*: inter-arrival time distribution based upon forecast of daily demand | Include | Required to model customer demand. *Extra: Also include arrival time slots if project time constraints allow* |
| *Attributes*: Order size, Order type | Include | Required for customer demand, and the two different order types require different loading processes |
| *Attributes*: Customer location, delivery deadline, batch-orders, delivery method | Exclude | Out-Scope, insufficient data available and/or irrelevant for project objectives. |
| *Routing*: to queue of compatible loading spot/dock | Include | Impacts queue waiting times & sizes |
| ***Activities*** | | |
| ***Loading process of order*** | | |
| *Quantity*: Number of available loading docks/spots per order type | Include | Determines nr. of process stations per order type & possible experimental factor |
| *Cycle time*: Variable time determined by total tonnage & order type | Include | Experimental factor (available capacity) |
| *Breakdown/repair* | Exclude | Insufficient available data, increases complexity and has limited impact on logistical throughput capacity. |
| *Set-up/changeover* | Include | Do have an impact on loading times, especially on bulk types. But no data is available. Therefore generally considered and simplified in the processing time. |
| *Resources*: Equipment is required to load orders | Include | Experimental factor (percentage of maximum available capacity during year) |
| *Shifts* | Include | One daily shift & brakes are not considered. Orders fulfilled after closing time are considered late. |
| *Routing* | Exclude | No routing required during the loading of order |
| ***Queues*** | | |
| ***Loading spot/dock*** | | |
| *Quantity*: 1 per order type | Include | One for each order type so assess individual order type performance |
| *Capacity*: unlimited | Exclude | No limit for waiting orders |
| *Dwell time* | Exclude | Not applicable to problem |
| *Queue discipline*: First In, First Out | Include | Could differentiate between Agrifirm & Triferto orders for sake of OTIF performance, but not applicable to this simulation model. |
| *Routing*: to first available & compatible loading spot/dock | Include | Loading spots/docks can load one of two order types. |

| | | |
|---|---|---|
| ***Resources*** | | |
| ***Equipment*** | | |
| *Quantity* | Include | Varies during the year due to other processes like production requiring equipment. |
| *Where required* | Exclude | Drastically increases project complexity. All stations have according to equipment available |
| *Shifts* | Exclude | Equipment is always available |

## B.6 Modelling Assumptions

| ***Category*** | ***Assumption*** |
|---|---|
| Order size | Both order types have their own order size distribution.<br>Based upon both theoretical (Weibull) and empirical distributions. |
| Order arrival process | Both order types have their own arrival process.<br>Is according to a Poisson arrival process where inter-arrival times can vary during the day. |
| Daily demand | Daily demand in tonnage for each order type is based upon a typical day of that week in the forecast. |
| Available throughput capacity<br>The number of loading stations stays the same throughout the year for each facility. | Modelled throughout the year as a percentage of the maximum available capacity of the facility. |

## B.7 Model Simplifications

| ***Category*** | ***Simplification*** |
|---|---|
| Secondary activities | Secondary activities like; order check-in/check-out, weighing order load, changeovers, order movements over facility and detailed loading activities are not individually modelled. They are considered in determining the total available loading capacity.<br>No variation in loading time other than seasonal loading capacity. |
| Order batching | Not considered in the model due to it not having an impact due to the simplification of secondary activities. |
| (Loading) equipment | Are always available, but are considered in the available capacity determination. |
| Employees | Enough employees with sufficient skills are available. |
| Product portfolio | Only differentiate between order types (bulk & bagged), not specific products.<br>Always sufficient inventory to fulfil orders. |

## B.8 Data requirements

| ***Category*** | ***Requirements*** |
|---|---|
| Demand data | Daily demand throughout the year (forecast) of each order type for each facility.<br>Order size distributions for each order type.<br>Arrival intensity distribution throughout the day for each order type. |
| Loading process | Maximum logistical throughput capacity of each facility.<br>Available maximum logistical throughput capacity throughout the year.<br>Number of available loading stations for each order type for each facility. |

# Appendix C

# Order generation within the simulation model

## C.1 Historical and modelled distributions

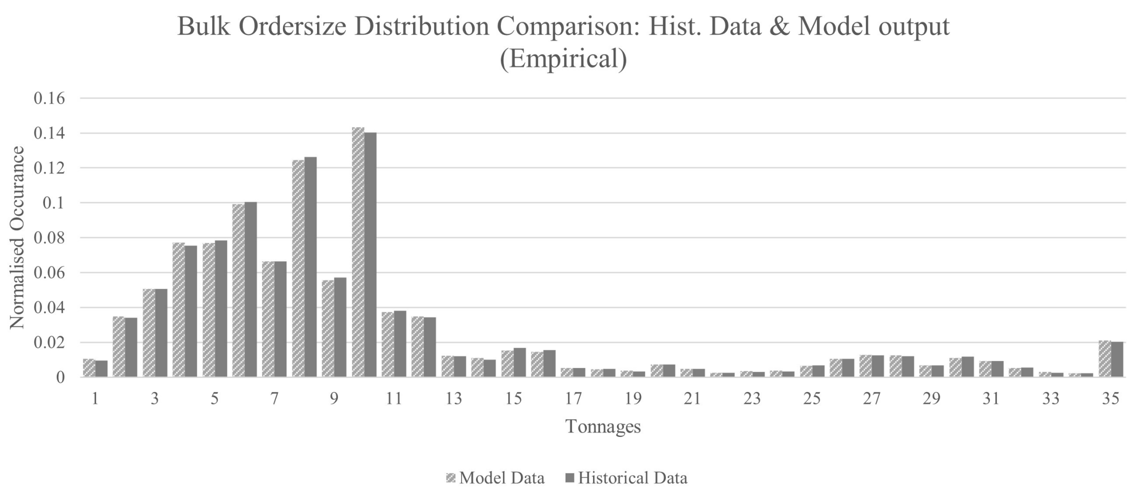



Figure C.1: Bulk Ordersize Comparison

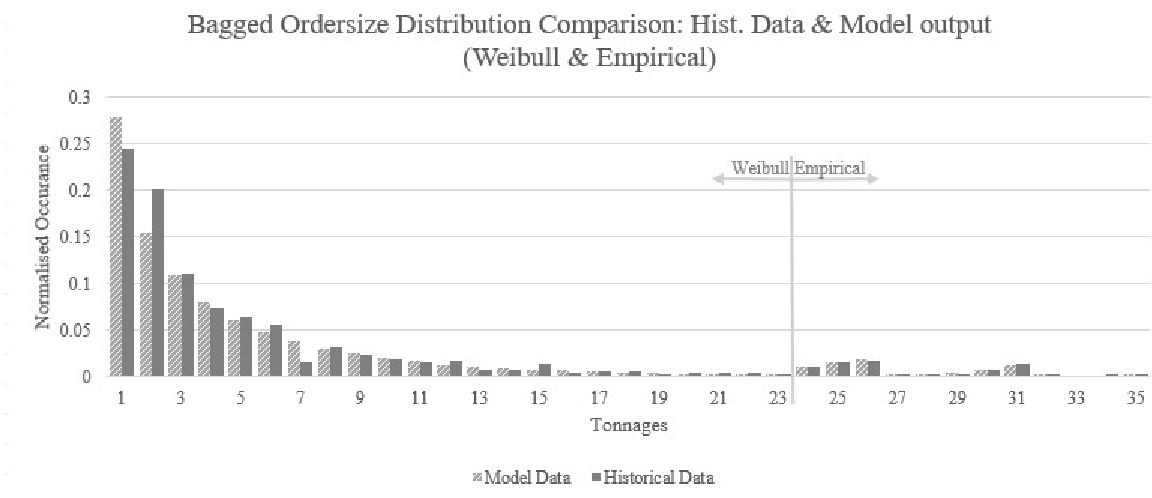



Figure C.2: Bagged Ordersize Comparison

# Appendix D

# Verification and Validation of a Simulation study

Verification and validation of a simulation model are processes that help to ensure that the simulation models are correctly built and reliable. This appendix explains how we can verify and validate a simulation model. Terminology in the area of verification and validation used to vary over different studies (Kleijnen, 1995). However, over time the definition of the two became more standard as shown in more recent literature; see D. K. Pace 2004, R. G. Sargent 2010 and A. M. Law 2015. Verification is determining if the simulation model performs as intended, for example, it being bug-free. Validation is determining if the simulation model is an accurate representation of the real-world system it simulates, for the particular objectives of the study. The following list explains some of the commonly used verification and validation techniques which are also relevant to this research.

- *Animation:* By comparing graphical animations of the simulation model with the real-world system as it moves through time, e.g. truck movements on the locations.
- *Event Validity:* The events that happen in the model are compared to those of the real system to see if they are reasonable. For example the average total amount of tonnages loaded during a day.
- *Extreme Condition Tests:* Outputs of the model should be plausible when using extreme input or parameters. For example, the utilization should be low if the processing time of an order is very quick and demand is normal.
- *Face Validity:* Relevant stakeholders are asked whether the (conceptual) model, its behaviour and/or outputs are reasonable and reflect the real-world system correctly.
- *Internal Validity:* Several runs of the simulation model are executed to determine the variability within the model. A large amount of variability of the output variables with the same input could cause the results being questionable. When this is typical for the model, one can question the appropriateness of the policy or system being researched.
- *Operational Graphics:* Various performance measures like loading dock utilization, average waiting time, overtime, etc. are shown graphically as the model runs through time to monitor if they behave correctly.
- *Parameter Variability & Sensitivity analysis:* A sensitivity analysis tests individual input variables on their sensitivity by determining their effect on the output variables. These relations should be the same as in the real-world system. An input variable is considered sensitive when is the impact on the output variables is relatively large. To make the model more valid, these sensitive variables could be made sufficiently accurate in the model, but these variables could also indicate that they should be carefully managed in the real-world system.
- *Traces:* Following specific individual entities throughout the model and see if they behave as expected to access the model's logic and accuracy.