MASTERARBEIT / MASTER'S THESIS

Titel der Masterarbeit / Title of the Master's Thesis

„Simulation of a two region multi-depot pickup and delivery problem"

verfasst von / submitted by

Miriam Dierks, BSc

angestrebter akademischer Grad / in partial fulfillment of the requirements for the degree of

Master of Science (MSc)

Wien, 2017

Studienkennzahl lt. Studienblatt / degree programme code as it appears on the student record sheet:	A 066 915
Studienrichtung lt. Studienblatt / degree programme as it appears on the student record sheet:	Masterstudium Betriebswirtschaft
Betreut von / Supervisor:	o.Univ.Prof.Dipl-Ing.Dr. Richard F. Hartl
Mitbetreut von / Co-Supervisor:	Dr. Margaretha Gansterer

Acknowledgement

I would like to say thank you to the Production and Operation Management Department of the University of Vienna, especially to Mr. o.Univ-Prof.Dipl-Ing.Dr. Richard Hartl, who gave me the opportunity to work together with Mrs. Dr. Margaretha Gansterer on a study for a research project. It was such an excellent experience to work with the data from the research team to implement stochastics into their deterministic model and to present the outcome data and analysis. As well my thanks go to Alina Dragomir from the FEAT-Team who provided the data to me.

Further gratitude is extended to Dr. Roland Braune, who supported me in creating the complicated simulation model to implement the data of the research team. Without his encouragement I would not have been able to complete the model.

Finally, without my sister and friends, I would not have finished my studies or be as satisfied as I am now with this achievement.

List of Tables

List of Figures

List of Abbreviations

SD	Standard Deviation
TW	Time Window
CV	Coefficient of Variation
MD	Miriam Dierks
FIFO	First In First Out
POM	Production and Operations Management
VRP	Vehicle Routing Problem
VRPB	Vehicle Routing Problem with Backhauls

Table of Contents

1. Introduction

This master thesis is based on a research project called FEAT: Fair and efficient allocation of transportation. One particular area of this project, a two cluster problem, was assigned to be analyzed with stochastics. The main steps taken during the thesis were as follows: literary research, creation of a simulation model, analysis of data and progress towards a conclusion.

1.1. Problem statement

Globalization brings more opportunities to import or export goods and to overcome long distances. To optimize the logistic behind the huge network and between carriers to stay competitive, new strategies have to be found to handle goods in a timely and satisfying way, keeping the customer and employees in mind.

Science departments focus on, and invent optimization programs to gain more efficiency within the transportation problems, mainly with a deterministic approach to get feasible solutions and optimal results. They work with deterministic models, because it is difficult to integrate uncertainty and probability into the complex models and accomplish latest insights of logistic barriers and invent new procedures without considering uncertainty of events.

The main purposes of this project are to highlight the ways in which optimal deterministic solutions and its routes, which are already found, behave within a stochastic environment, regarding to service level and travel time.

The main purposes of this project are to highlight the ways in which optimal deterministic solutions and its routes behave with stochastic influence in service level and travel time.

1.2. Theoretical Background

Due to increasing globalization and specialization, distribution networks expand geographically so that consumers are now further away from producers (Caris, Macharis, & Janssens, 2008). Fast and reliable movements of products and raw materials from the place of production to the place of consumption are essential to ensure successful busi-

ness. Freight transportation makes it possible to meet the increasing demand for transport. Moreover, it also entailed an increment of competitors and major difficulties for shippers, carriers, and Logistics Service Providers to stay competitive within the market.
However, the emerging trends in transportation also stipulate that shippers, carriers, and Logistics Service Providers have to reduce their expenses while continuing to deliver high quality standards (SteadieSeifi et al., 2013).
Even in the early stage of multimodal transportation, Nozick and Morlok (1997) invented a model for train-truck operations to have consistent quality in delivery and better cost-effective use of resources in the tactical time phase of planning. As a result, carriers and other Logistic Suppliers look for new ways to allocate resources more economically. By using multimodal transportation, freight transportation can be even more efficient, reliable, flexible, and sustainable. (SteadieSeifi et al., 2013).

For the most part, a multimodal transportation chain is divided into three parts, the pre-haul, the long-haul finally the end-haul of a tour. The first as well as the last element display the pickup or delivery of goods to the customer. The long-haul transportation consists of longer distances than the other two elements. To overcome the distances, not only trucks are used but also other modes such as trains, ships, or airplanes (SteadieSeifi et al., 2013). With multimodal freight transportation a minimum of two modes within the chain are selected to transport the goods (Khou Sid'Ahmed, 2009).

Macharis and Bontekoning (2003) stated that the main emphasis of Operational Research is still on uni-modal transportation and neglects mulitmodal transportation problems, although multimodal transportation has become more and more important recently. On that account, they examined the existing literature to approach the neglected areas. Because multimodal transportation is such a new subject in transportation research, there are a lot of papers covering this topic, but without any significant improvements (Caris, Macharis, & Janssens, 2008). Caris, Macharis and Janssens (2008) stated that due to the presence of several decision makers, who are all involved in the operations, more coordination is necessary. Support tools may support the decision makers to improve their operations. The amendment to the above statement in the latest paper of Caris, Macharis and Janssens (2013) showed that Operations

Research with regard to the development of decision making tools had a positive impact and an increase in papers compared to the recent years. In general, the planning problems for multimodal transportations are sophiscitated due to the different combination of modes, stakeholders and diverse sizes of cargo accentuated by the authors.

Stakeholders at various positions of the multimodal transportation chain have to make decisions (SteadieSeifi et al., 2013) at three planning levels which have their own time scales: strategic, tactical, and operational planning (Crainic & Laporte, 1997; Caris, Macharis, & Janssens, 2008; SteadieSeifi et al., 2013).
Strategic planning is a long term decision and involves financial resources to build and plan the actual structure of the network (Caris, Macharis, & Janssens, 2008). The generic framework of transport network designs at the strategic level is quoted in detail by Woxenius (2007). Hub-and-spoke network and five other designs were examined by the author, considering the operational attributes to freight and rail transportation (Woxenius, 2007; Caris, Macharis, & Janssens, 2008).

1.2.1. Hub-and-spoke Network

In general, the transportation method Hub-and-spoke is a system where a connection between two or more nodes (Depot) is not directly linked to each other; instead they go to a central node (Hub) and from whence it gets further distributed. The model was invented with regard to shipments, to speed up delivery and save transportation cost by reducing empty (return) routes. The figure shows a single Hub-and-spoke network.

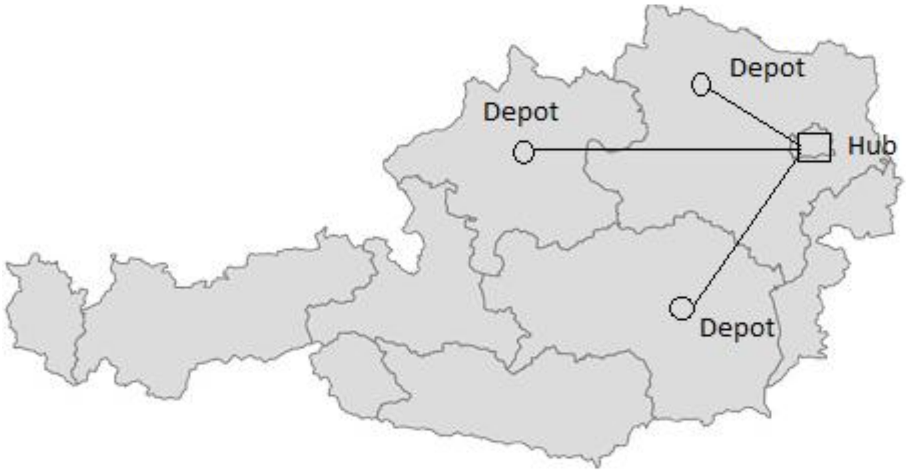

Figure 1: Hub-and-spoke Transportation Problem

In view of the FEAT research project, they used a more complex and detailed Hub-and-spoke model, with more than one depot connected with a long haul connection. The long haul connection has to be planned by the carrier. Additional constraints like TW, regular delivery with different planning prospects, capacity and fleet restriction were included. The figure shows two carriers, each with two depots, all connected with long haul transportation.

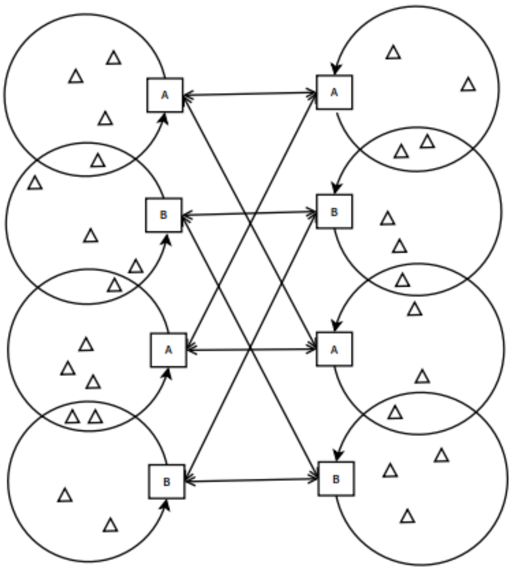

Figure 2: Hub-and-spoke with two carries and hubs

The above described Hub-and-spoke model was than transformed to fit with the complex transportation and the world-wide system to a model that shows the collaborative scenario. It includes the interaction between multiple carriers to reduce empty tours.

Woxeniux (2007) highlighted that the main advantage of hub-and-spoke networks is to link up various pick-up and delivery targets with a high frequency, albeit with light loads. This can be done only with two links. The result is overcoming further distances (Ishfaq & Sox, 2012), a better use of resources and storage facilities could be outsourced to the terminals of transshipment if no time windows are involved. This system joins all nodes into the hub but it needs an efficient time management to quickly transfer all requests into the appropriate directions.

Although a hub-and-spoke network has its positive effects on yield increase, it could have a negative impact on the service level if delays at the hub through shipments arise. This could arise if arrivals of shipments are too frequent and the recourses at the hub are unable to handle it in time and queues build up. These queues increase the shipment time at the hub. With a higher fluctuation in waiting time of shipments, an uncertainty will rise and this will lead to queues build-up and delays, which worries the carriers because delays influence the further distribution by the carrier and can lead to a drop in service level. (Ishfaq & Sox, 2012). Furthermore Andersen and Christiansen (2009) invented a model to observe the service level affected by rail-based cargo.

To make better decisions on investments at the strategic level, the network operator must select the appropriate consolidation network, for which discrete-event simulation modeling can be a helpful tool. This tool can investigate how the multimodal transportation problem with its movement of vehicles, trains, cargo and long haul transportation and transshipment of cargo with various modes, interact and work most efficiently (Caris, Macharis, & Janssens, 2008).

1.2.2. Tactical Horizon Level with Multimodal Transportation

The next horizon is tactical planning with a medium time scale, which has its focus on the enhancement of productivity of the existing system by using financial resources successful and accordingly (Caris, Macharis, & Janssens, 2008). A main tactical problem for a multimodal transportation problem is the service network design (Crainic & Laporte, 1997). On this subject the materialization is to allocate demands to vehicles and determine routes and the specific service features (Caris, Macharis, & Janssens, 2008). According to the transportation plan a relocation of used equipment is planned economically, selecting services and the required kind of transportation with the respective capacities of the assignments as well as the designing of routes and its interval rate (Caris, Macharis, & Janssens, 2008; SteadieSeifi et al., 2013) for the upcoming timescale, loads have to be efficiently scheduled to avoid empty tours (Caris, Macharis, & Janssens, 2008).

When optimizing a multimodal transportation problem, Sitek and Wikarek (2012) analyse the whole supply chain through the eyes of a logistics provider, and thus manage to include all elements of the chain into the Linear Programming.
Similarly, at the tactical level, a service network, which was presented at the strategic level by Woxenius, 2007, has to be chosen to by a network operator for multimodal transportation. There is a lack of research in the area of designing service networks at this level to support the decision making process (Caris, Macharis, & Janssens, 2013). In particular, the decision on the consolidation strategy, as to how to best dispatch the load, either direct or via multimodal transportation, balances upon the aspects of demands, expenditure of used system, network construction and processing times which need to be balanced optimically. Generally in the literature used, for a service network, the hub-and-spoke model is applied. (SteadieSeifi et al., 2013). The purpose of a hub-and-spoke network is to transport cargo with a service from one terminal to the next. Service is marked by many components like pickup and delivery destinations, hubs, the mode and capacity, as well the tour, whereas the cost of the mode and its constraints like travel time and capacity must be taken into consideration. (SteadieSeifi et al., 2013)

In their paper, Tsamboulas, Vrenken and Lekka (2007) explored the modal shift of transport from road to multimodal transportation, with the focus on the change to rail. They modified the essential tools to accomplish the modal shift, dealing with topics vis-à-vis service, as well as the relationship between cargo transportation strategy and supply chain features and activites. Lin and Chen (2001) have a similar but more operational approach to the problem of choosing the right mode. They consider a more specific problem set of delivering minor amount of goods via express service and facing the problem of tight time windows with completion of a high service level. They used a hub-and-spoke network with primary and secondary routes. At the depot they extend out to the origins or destinations, each depot is linked with its prior hub with a secondary route. The primary route joints the hubs, where the cargo is picked up. To solve the problem of time windows, a hierachical hub-and-spoke network is applied to assign the needed vehicles and time tables either to a primary or a secondary route. The objective function is to fulfill the required service level with a minimum expenditure. The approach of reallocation of primary or secondary routes resulted in an appropriate planning tool for operators. The outcome showed that reaching a higher service level does not mean having accordingly higher costs to the same extent.

In the early stage of research, Ziliaskopoulos and Wardell (2000) bore the area of multimodal transportation in mind, in particular with regard to transit and freight. At changing modes, the impact on travel time and its changing state to the network was noted. They examined the network with its varying terms alongside the different kinds of transportation, and displayed a complex algorithm to optimize the interaction between them. The algorithm takes into account routes, hold-ups and the related waiting times.

In their paper on the subject, the Authors Hamzaoui and Ben-Ayed (2011) elaborate a model to make efficient departure schedules for small packet allocation with hub-and-spoke transportation networks. The main problems are the time windows for the delivery to the customers and arrival rate at the terminals. The success of the delivery of goods from the sender to its destination depends on the efficiently planned routes. For the distribution a hub-and-spoke is used to save money by amalgamating goods at the hubs and transport it directly to other hubs to overcome longer distances. To collect or deliver to the customer, the tour starts at the depot and proceeds from customer to customer inter-exchanging varying quanity on a limited basis and subsequently returns to the depot . To build the model, the service level is set constant to maintain a garuanteed delivery of the packages to help the making of tactical decisions and to get an efficient departure schedule with the objective of minimizing cost and not dropping the service level (Hamzaoui & Ben-Ayed, 2011).

Another aspect is the travel time and its information, used to forecast the unseen. Demeyer et al. (2013) wrote a case study on the behavior with dynamic and stochastic travel time information because the travel time depends on traffic during the day. The aim was to have a practical approach and glean reliable routes accounting for the uncertainty. The outcome of the case study highlighted that multimodal networks perform better than unimodal ones. The influence of uncertainty was also analyzed by SteadieSeifi et al. (2013) in their paper because if it is ignored it could hinder success in proceedings. A steady transportation network has to cope with the uncertainty factors, like forces of nature or congestion or unexpected collisions and this makes the planning very complex and difficult. If the system is not adaptive to the malfunctions, recovery plans for service and modal transportaion has to be introduced to provide the same service. Some authors like Miller-Hooks et al. (2012) introduced simulation models to their problem set to best handle potential unexpected events to insure adaptive operation. A Monte Carlo simulation was applied to incorporate the different crisis executions and to ascertain their behaviour. Preparing well beforehand and investing money into the backup plan for unexpected incidents, ensures a better outcome on proceedings (SteadieSeifi et al., 2013).

To investigate uncertainty, Meng et al. (2014) highlight the influence on travelers choices with a stochastic model in their paper. The effect of happenstantiall errors upon a travelers´ perception arising from a lack of information results in travellers choosing the best route with a mimimum cost. when traveling with various transportation systems were analyzed by Meng et al (2014). As a result, travelers prefer combined transportation means but the factor risk had an opposite influence on decision making. Furthermore, Caris et al. (2012) used simulation to gain further insights in a corridor network designed to deal with terminals and its grouping in Belgium.

In the short term horizon, uncertainty has a huge influence on planning issues and characterizes the real world problems when planning routes with last minute influential and changing environmental factors (Dube, Goncalves, Mahatma, Barahona, Naphade, & Bedeman, 2014). In Winter 2014, a simulation conference took place to approach the uncertainty in multimodal transportation problems as it is still a very strenous issue. To support the operations in decision making, helpful tools are needed - on the one hand;

to cope with the continuous haul optimization and planning to tackle specific restriction of timings, capacity and coverage; and on the other, to include all kinds of commercial laws like conventional contracts or market circumstances. An analytictcal simulation program to support it all was presented. (Dube, Goncalves, Mahatma, Barahona, Naphade, & Bedeman, 2014).

1.3. Simulation Modeling

The easiest and most effective means of bringing stochastics into a deterministic route problem is to use simulation models. Simulation modeling allows the creation of a real-world problem with probability distributions and thereby to imitate the problem over time. Sometimes it is too effortful or even impossible to experiment with real objects for several reasons as, for example, danger or expense. In such cases, simulation modeling is used to build a model of the real world in a less complex way (Borshchev, 2013).

Although analytical models have a lot of advantages and are easier to use, there are some circumstances where a solution cannot be found analytically. Especially, if a problem includes uncertainty or uncertain behaviors, analytical modeling fails to work and simulation modeling is used instead. By using simulation, it is also possible to add measurements and statistical analysis to the model at any time. There is a wide range of areas where simulation modeling is used and one such area is transportation (Borshchev, 2013).

There are three methods of simulation modeling, namely system dynamics, discrete event modeling and agent based modeling. System dynamics can be used for strategic modeling like introducing a new product on the market. Discrete event modeling displays physical objects to model the process e.g. a production line. With agent based modeling, agents can have certain behaviors and act on it like customers, vehicles or companies. Agents can also communicate and interact with each other (Borshchev, 2013).

To build a simulation model that suits a given problem set, the level of abstraction need to be considered to choose the correct method of modeling. System dynamics is used when the level of abstraction is high and discrete event modeling when there is a low-medium abstraction. Agent based modeling is somewhere in-between and can integrate both. A transportation problem has a medium abstraction level (Borshchev, 2013).

1.4. Methodology

In this master thesis, the simulation software Anylogic 7.0.3 University was used to build the simulation model. During the project the license of the University expired and Anylogic 7.3.7 Personal Learning Edition was used in its place.

First and foremost, the theoretical background of multimodal transportation and simulation was described in chapter 1, then, in chapter 2, the planning problem with all the used data from the research team will be described. Chapter 3 gives an overview of the simulation model and how it was built, upon which Chapter 4 continues, by including all the output and the analysis of the main objectives, namely service level, cluster cost and travel time. Finally, chapter 5 contains the conclusion and an applicatory outlook at the simulation model along with its potential applications.

2. Research Project FEAT: Fair and Efficient Allocation of Transportation

Due to the high competition in the shipping and transportation industry, profit margins of transportation carriers, who fulfill transport requests for other parties, have declined to an extremely low level (Vetschera, Doerner, & Gansterer, 2014). To stay in business, carriers need to avoid empty trips that cause costs and reduce profits rather than generate revenue and thereby a higher level of efficiency. To improve overall efficiency, transport requests could be re-allocated among carriers to avoid such costly empty trips (Gansterer & Hartl, 2016).

A recent research project called FEAT: Fair and Efficient Allocation of Transportation, aims to address this issue by studying collaborative mechanisms to re-allocate trips between carriers. The main goal of this project is to increase the system-wide efficiency of the transport industry by improving both the planning process of individual carriers, and the collaborative re-allocation of transport requests to carriers (Vetschera, Doerner, & Gansterer, 2014).

As the project is established in the field of transportation research, it requires the integration of experts from various fields. On that account, the research team involved in the FEAT project consists of several researchers from three different departments of the University of Vienna, the Chair of Production and Operations Management (POM), the Research Group Organization, Personnel and International Management (OPIM) and the Chair of Production and Logistics with international Focus (PLIF). Each group is responsible for one special problem, but they are also working together to compare the different collaboration mechanisms.

Overall, they aim to develop solution methods that improve the economic situation of carriers by reducing empty trips and providing a more balanced and cost-effective transportation network that rather leads to positive profit margins. In addition, the developed solution methods should also improve the ecological situation, especially in Austria, where 27 % of the vehicle-kilometers are driven empty producing the emission of harmful substances, noise pollution and other negative externalities.

2.1. Motivation and Problem Structure

The motivation behind the study is the reduction of empty trips caused by the inefficient planning of tours in the transportation section, where one has two parties: the shipper and the carrier. This could be avoided by re-allocation of requests among carriers. As stated above, by avoiding empty trips with collaborative mechanisms the project team pursues both, economic and ecological goals and thus an improvement in the system-wide efficiency.

The project focuses on a realistic problem structure since the problem setting occurs in the real world. The problem setting is considered as a three-stage transportation setting with local trips modeled as a vehicle routing problem with backhauls. Within these trips, goods are delivered from customers to one of the two hubs a carrier has. Those hubs are connected by a long-haul transportation leg and goods are delivered from there to customers using local trips again.

Existing literature concentrates on individually developed approaches for collaboration instead of comparing the different solution approaches. With the FEAT project the researchers want to overcome the lack of systematic comparison by providing a comparative evaluation of different coordination mechanisms. Thus, they are developing a fully centralized planning approach as well as a centralized auction approach. In addition, they are analyzing a decentralized auction model and the bilateral exchange of requests between carriers.

To improve the whole system, an increase in communication and collaboration between carriers is necessary. To obtain better communication, higher flow of information is needed. In the end, there must be a trade-off between information exchange and efficiency gains. For this reason, the research team focuses on analyzing the consequences of information and its cost. The analysis of the four different coordination mechanisms for one common class of logistical problems is done by computational models, including not only the technical constrains, but also the issues of fairness and individual rationality.

2.2. FEAT Dataset

The whole research project was divided into smaller problem tasks that were assigned to various people. One of the problem tasks includes the planning of transportation of goods between two clusters. It can be classified as a vehicle routing problem with mixed linehauls and backhauls. First, goods are collected from customers and then go to the depot of the carrier (one cluster). Second, the goods are delivered from that depot to the depot of the other carrier (other cluster) via the long-haul transportation. Finally, the goods are delivered from the depot to customers.

Each request is assigned to a vehicle that has one or more tours, but every tour starts and ends at the depot. Every customer has time windows that must be satisfied. If a vehicle arrives too early it must wait until the time window begins. The goal is to minimize the total costs composed of the short-haul costs of both clusters and the long-haul transportation cost. It should be mentioned that the total cost for the long-haul cannot be fixed because it is fixed in advance. In addition, the number of outsourced requests should be minimized. Figure 3 shows all parameters used in this problem. Most of the parameters are used in the simulation model as well in order to develop a model that comes as close as possible to the deterministic solution generated with this approach.

.

shorthaul vehicles	m^A	=	number of shorthaul vehicles in cluster A,
	m^B	=	number of shorthaul vehicles in cluster B,
	Q	=	capacity of each shorthaul vehicle,
	T	=	maximum total route duration for each shorthaul vehicle,
longhaul vehicles	l	=	number of longhaul vehicles,
	H	=	travel time for longhaul transportation per direction,
	C	=	fix cost of longhaul transportation per direction,
	F	=	capacity of each longhaul vehicle,
	D	=	List in which cluster each longhaul vehicle starts
requests	n	=	number of requests,
	q	=	List of quantities demanded by each request
	AB	=	number of requests travelling from cluster A to cluster B,
	BA	=	number of requests travelling from cluster B to cluster A,
	directionAB	=	List of requests travelling from cluster A to B
	directionBA	=	List of requests travelling from cluster B to A
	qA	=	List of quantities in cluster A
	qB	=	List of quantities in cluster B
	eA, eB	=	Begin of time windows for each request in cluster A and B
	uA, uB	=	End of time windows for each request in cluster A and B
	dA, dB	=	distance matrix in cluster A and B
	cA, cB	=	cost matrix in cluster A and B
depot	d_eA, d_eB	=	earliest departure time from depot in cluster A and B
	d_uA, d_uB	=	latest arrival time at depot in cluster A and B
	p	=	total penalty for outsourcing a request,
	K	=	maximum number of tours for all shorthaul vehicles,

Additional parameters for the **fix instances:**

B = List with the number of single trips each longhaul vehicle is making,

h = departure time of all longhaul vehicle for each single trip

Additional parameters **flex instances:**

B = maximum number of single trips for all longhaul vehicles,

w = number of round trips for all longhaul vehicles with is $\frac{B}{2}$,

Figure 3: List of parameters FEAT-Problem (based on Dragomir et al. , 2017)

3. The Simulation Model

In this chapter, the modeling of the simulation model is described. To create a model that fits the stated problem set in chapter 2, a terminating type of simulation with a discrete event and agent based modeling was chosen. It is terminating due to the one-day operation of 1,440 minutes to complete the delivery of customer requests.

The main parts in the model are discrete, for example, building the element of the customer. Others needed an agent included, with its behavior respective to the model - mainly for the truck with its different activities like the TW or the difficulty of calculating the route. The whole model displays the main function of a Hub-and-spoke transportation problem, with only two clusters and two hubs, each having a depot.

All the input data of the FEAT Team is copied from a text file into Excel and called up via functions into the simulation model. The results of the output data are copied from the console of Anylogic into Excel.

3.1. Data used in the Simulation Model

Almost all parameters of the deterministic problem set are used in the simulation model to have a realistic outcome of data under almost the same condition as the deterministic version. However, only the additional parameters for the fix instances are used in the simulation model, the parameters for the flex instances are not used at all.

Due to the fact that the deterministic solution produced feasible and optimal routes which included the restriction of capacity, the maximum number of tours for the shorthaul vehicle, duration of tour, these parameters are not used: Q, T, F, K.

Some parameters did not influence the cost or the tour at all, therefore these were excluded. One example is the depot parameter for latest arrival at the depot “d_uA, d_uB” which was included into the model, but the parameter did not, in fact, influence the tour, because it had no restriction and the truck could return at any time. Another parameter is the cost matrix “cA, cB”, because they have the same values as the distance matrix. The penalty cost “p” for hiring external transportation was not incorporated due to the fact it is a fixed amount included into the cluster cost and could be calculated with great ease.

In total, there were nine different data sets applied. Each problem set has differing numbers in request, TW and distance matrix. The problems are categorized in different TW and the amount of customers. Three different kinds of TW are used. One is NO TW, where there are no restrictions involved. The other is Tight TW: here the customer has a medium-level restriction TW which makes it possible to reach the limited slot and fulfill the delivery. The last one is the SuperTight TW with a high-level restriction TW. The timings within the TW are very tight and close to each other, which makes it difficult to arrive the customer on time and complete the tour. All three problem sets have requests with 10 customers, another three sets with 25 and the last three with 50 customers.

An optimum solution which was generated by the FEAT Team with the given data and problem sets were applied to the simulation model as routes. The optimal routes are created by a deterministic method by the FEAT Team to solve the logistic problem of VRPB which are then used in the simulation model.
For each of the customer restrictions there is only one kind of distance matrix. The amount of requests of the customer stays constant within the customer restriction. The only exception is if transportation is outsourced and customers will be reduced.

All TW have a start and end time, the truck is bound to it and can start to unload if it is open, otherwise the truck must simply wait. If a truck arrives too late at the TW and it is closed, the tour has to skip the delivery and move on to the next customer. Depending on the level of restriction of the TW, the truck may have wider or narrower windows to reach the TW. Long haul transportation has start times allocated to the cluster where it starts and an allocated travel time for each direction. The parameter of a truck dictating the earliest time it can leave the depot and to start its tour is given by the FEAT data, this parameter changes when the recourse action II is applied and does not concur with the original data of the FEAT team.

3.2. Stochastics in the Simulation Model

To create randomness in a simulation model there are two main contributing factors. One is the option of using the probability distribution function and the other the random number generator. Anylogic has internal sources of randomness; different outputs are gleaned with every run even when maintaining the same parameters. For process modeling, the Enterprise Library has the Object "Delay" with integrated randomness. Every time the delay function is used, the probability distribution function is called and executed. Over the entire run, the driving time varies randomly from one occasion to another (Borshchev, 2013).

The other contribution is the random number generators which produce pseudo-randomness; without the computational generation there is no randomness at all in the model. From a primary value, the seed, a sequence of numbers is produced with an algorithm which results in random numbers. Only with the random number generator does the object "Delay" obtain its randomness (Borshchev, 2013).

To introduce stochastics into the deterministic figures, the object of driving time was chosen to gain randomness. There are two objectives which have driving time, one given by the distance matrix of the trucks serving the cluster and the other the driving time of the long haul transportation. The reason for these objectives is because in reality both modes can have delays caused by traffic jams, temporary closure of streets, break downs or human error. This kind of uncertainty is included into the simulation model with different variation factors: 5%, 10%, 20%, 25% and 30%.

Probability Distribution Function

To select the correct probability distribution function, a distribution fitting with the input data has to be done with *"fitting heuristics and goodness-of-fit tests"* (Borshchev, 2013). In this case there was limited data available and a uniform distribution with a (min, max) value was selected. With this kind of distribution (as there is only one number available) the travel time and this value can vary upwards and downwards depending on the variation level. No outcome between the minimum and the maximum are known and the distribution chooses any value without any preference between them.

3.3. Analysis Objectives and Method

Overall customer view: customers use logistics companies to get their goods where and when they are needed. The aim of Logistics companies is to supply goods to customers in a timely manner with up to a 100 percent satisfaction rate. If a delivery does not reach its destination in time or completely fails to do so, the customer will look for a different company. Losing customers lead to less revenue and more costs through the attempted acquisition of new ones.

Transportation expenditure has to be calculated efficiently to stay profitable within a growing market. Major cost factors in the transportation business are labor, maintenance charges and equipment. Profit can be raised by lowering costs when reducing, for example, empty tours, waiting time and number of vehicles in the fleet.

3.3.1. Objectives

There are three main objectives in serving the aims of customers and companies: service level, cluster cost and travel time. The notation and its explanation are described in this section.

"Service level" focuses on fulfillment of requests and highlights the intensity of completion with the given tour. It is the most important objective because if the fulfillment of the route is under 100 percent, it is not feasible – therefore, the main goal is to have feasible routes. If a route can not reach the designated bench mark, recourse action has to be applied.

A cluster is a definition for a group of customers who are close together. The definition of **"Cluster cost"** is to add all costs which are needed to complete the delivery within the cluster. In the case of FEAT, it is the cost of the train, the driving time of all trucks within the cluster and the outsourcing cost. To simplify the analysis and to obtain a more accurate conclusion, cluster cost included only the driving time of the truck within the cluster. More precisely, it is the distance from the depot (0) to the customer, to the next customer or back to the depot (0). The distance is given by a distance matrix from the FEAT Team. All distances are calculated together and the outcome is the cluster cost.

The last objective is the **“Travel time”** which includes the cluster cost plus all waiting time. The time is measured from the truck’s starting position at the beginning of a tour at the depot until it returns back to the depot and completes the assignment. This objective highlights the actual waiting time between the customers and depot.

3.3.2. Comparison Area for the Analysis

To compare the results within the data sets and to analyze the output, two main comparison areas are chosen. One is the request level of 10, 25 and 50 customers and the other is the various time windows with the restrictions of No TW, TightTW and SuperTightTW. This was selected to deduce how the results behave within one constellation: what kind of impact the TW has on the completion area and to the travel time. The other factor to examine is how the size of customers has an impact on all three objectives.

3.3.3. Analysis Output Data

The output data is valued at assessed objectives and the comparison areas. The given deterministic routes are applied to the simulation model and run with all of the different constraints. The results with extreme differences were subsequently discussed. The points of interest within one comparison area are examined and presented which were supported with graphs.

For all simulation runs with the diverse data sets, a check of feasibility of tours was applied. The sensibility of output data to the variation level also needed to be analyzed to predict the level of influence on the service level caused by uncertainty to the routes. All of the output data is kept for records and only the most interesting results for the master thesis are highlighted and explored in section 4.

3.4. Process Modeling Library

The discrete event uses the tools of the Process Modeling Library which offers a huge package of built in functions. The picture below presents the labels of the Library. Further details including a description of each item can be found in **Appendix C. Process Modeling Library**.

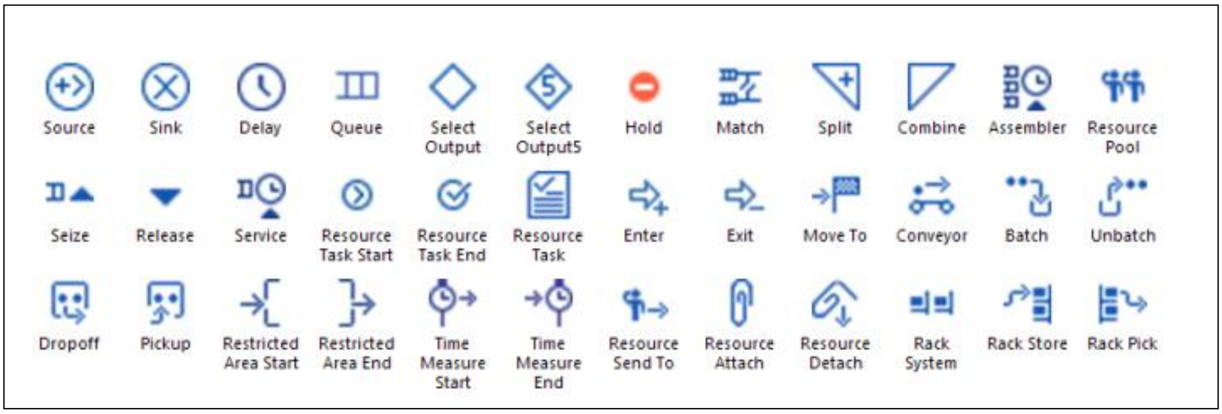

Figure 4 "Labels of Process Modeling Library" (Martins, 2015)

3.5. Simulation Model Overview

In MAIN of Anylogic the general logistics problem was modeled with discrete events of the Process Modeling Library. The whole model includes two depots A and B, two train stations A and B and two cluster of customer A and B. The cluster is connected with a truck based at the depot which picks up and delivers the goods. The long haul connection, a train, transports the bundled cargo from cluster A to B or vice versa. The train stations themselves are connected to the depot with a vehicle to transport the goods from the depot to the train station. The depot itself has a storage system which is handled by forklifts and can be adjusted to include operation of a warehouse management.

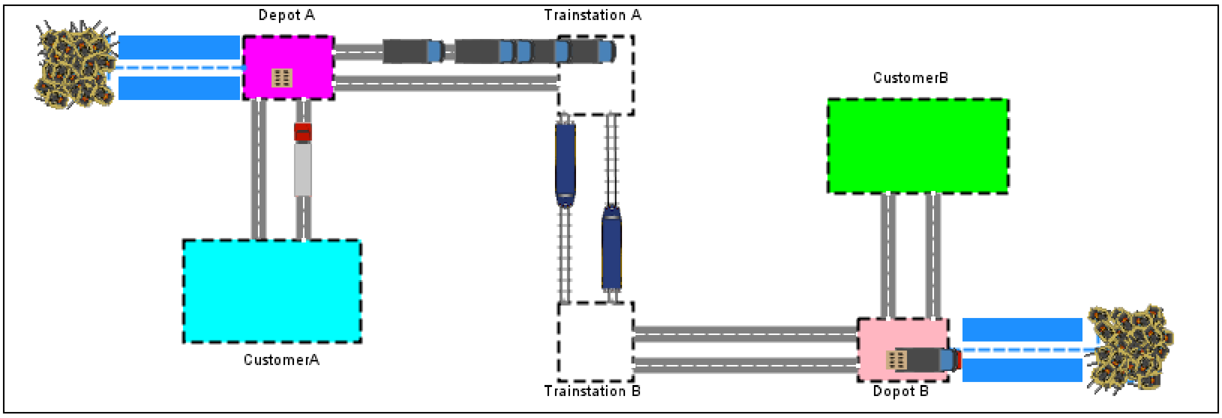

Figure 5: Simulation model two clusters with multi-epot network

3.6. MAIN of Simulation Model

For the truck which has its start and end at the depot, a discrete model is created with the Process Modeling Library and linked to an Agent **Customer**. With this integration of the Agent, all customers can be visited on the tour. The process looping of the vehicle moving from the depot A/B to the train station A/B, as well the train itself is built with discrete modeling in MAIN.

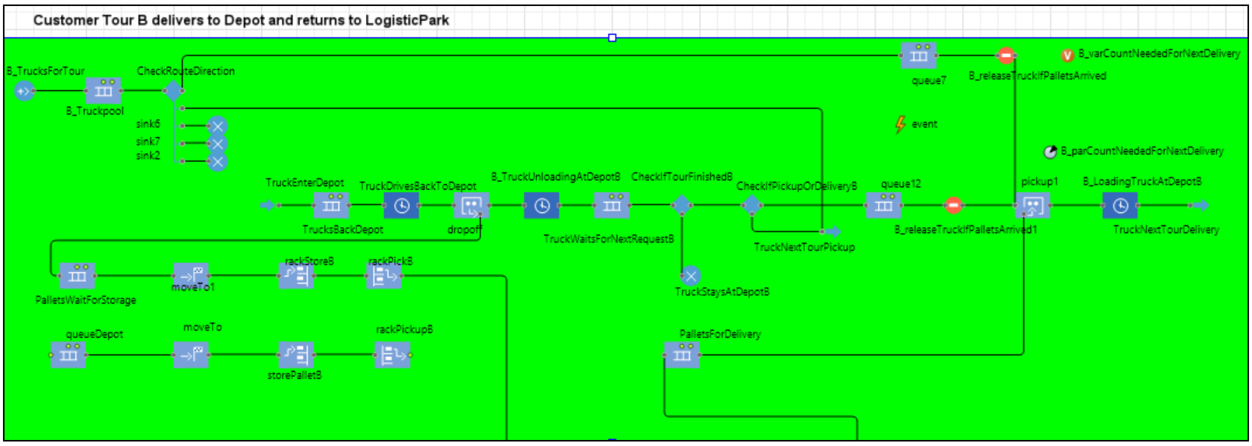

Figure 6: MAIN discrete Model of Depot B

The process shown in Figure 6 generates the required trucks which start and end the planned tour at the depot. The truck must either wait at the depot to load goods to be delivered, or it can start to collect the goods from the customers. After the collection of goods, it returns back to the depot, drops off the load and continues the route or if the tour finished stays at the depot. The delivered goods get dropped off into the warehouse system and stay there until the vehicle arrives and picks up the goods and brings it to the long haul (train) station. In this case there is no travel time between the depot and the train station and the goods get “beamed” to its destination. The same vehicle picks up goods from the train station upon arrival and transports them to the depot where normally a storage system is integrated. In this special case it is not in use because of the deterministic restriction that goods are “beamed” into the truck and therefore there would be time differences to the deterministic solution.

The pickup facility of cargo at the depot operates with a release function. The release of a truck is carried out with the FIFO procedure. The first truck that enters the queue will

be served first. A further condition is integrated into the model. The higher priority of receiving the goods first for delivery gets the truck which starts its tour with a delivery task “B_releaseTruckPalletsArrived”. When this queue is empty and has no more trucks waiting, the other truck which returns back from its tour to the depot and waits to get goods for delivery “B_releaseTruckPalletsArrived1” will be served.
The parameters of section 2.2 are integrated into the depot model to get the same conditions as for the deterministic problem.

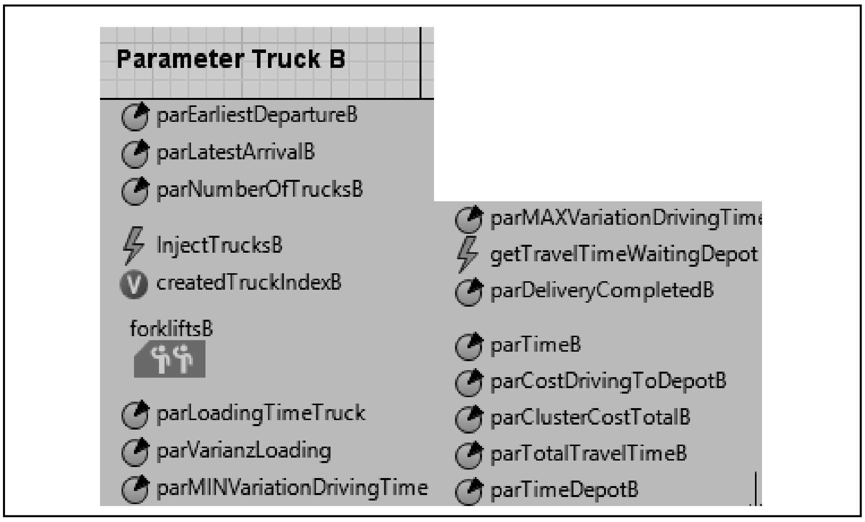

Figure 7: Truck parameter and restrictions in the Simulation model

Additionally to the parameters given by the research project, there are some further parameters created to save the different timings of the truck traveling and to calculate the cost.

3.7. Agents of Simulation Model

There are different kinds of agents built into the model to make the model run with all its constraints and inputs. An important role is placed with the customer and truck, but there are also agents for the train, vehicle, goods (pallet) and forklift.
The agent customer and truck is explained in detail in the next section to get a better insight of the important operation within the model and its purpose.

3.7.1. Customer Agent

To fulfill the delivery for all the customers with its TW, a discrete event with its element from the Process Modeling Library is modeled. It displays the whole process starting with the driving of the truck to the actual customer and the delivery itself.

The truck either goes from customer to customer, or returns back to the depot. There are functions of the truck integrated within the delay components to get the required information. For example, the delay of the TW calls the function, which is integrated into the truck agent to calculate if either the TW open or closed, or if the truck has to wait, the length of time it has to wait at the customer before the TW opens up again.

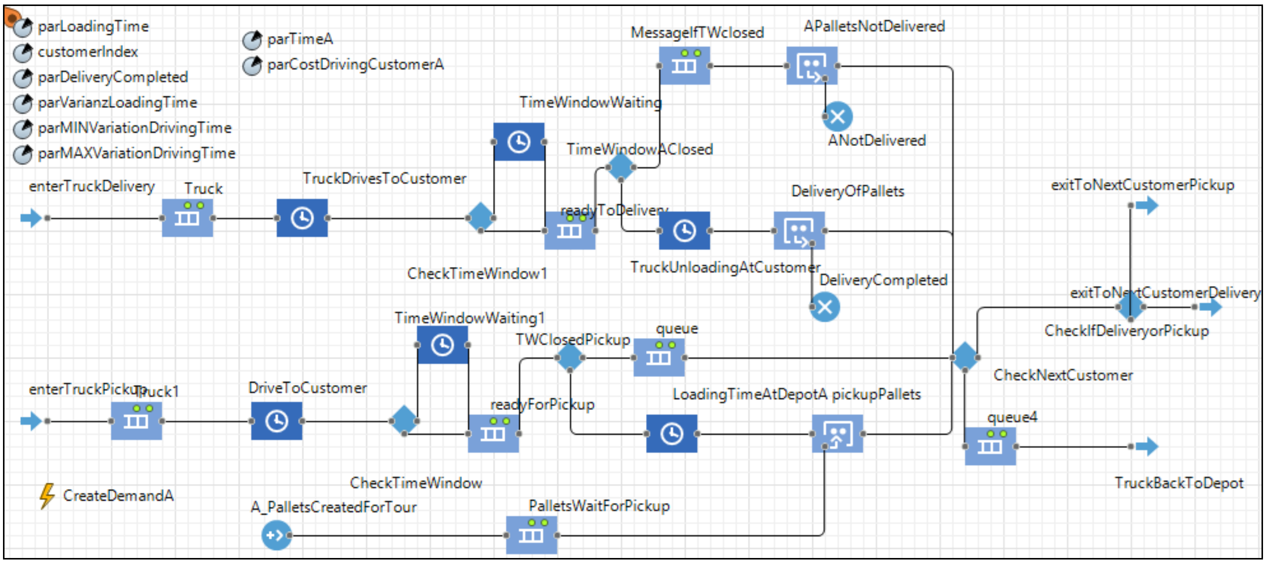

Figure 8: Agent of Customer A with it pick up or delivery process

As well the goods of the different customers are inserted at this point calling the variable of the truck agent. For each customer a separate Agent is created.

3.7.2. Truck Agent

Another agent is the truck with all the data saved from the FEAT Team and its function is to follow the given route and create the demand for the cluster and deliver the goods. This agent holds all needed information to complete a given tour, for example the driving time of the distance matrix, time windows, quantities and the route itself. The amount of agents is adjusted to the specification of the FEAT Team and because choosing an Agent type, multiple routes are able to be driven at the same time.

The variables “Quantities”, “DistanceMatrix”, “Tour” and “AllToursAB” are implemented to save the data received from Excel. The parameters have the goal of achieving a differentiation between the various trucks and to keep a track of the progress of the route.

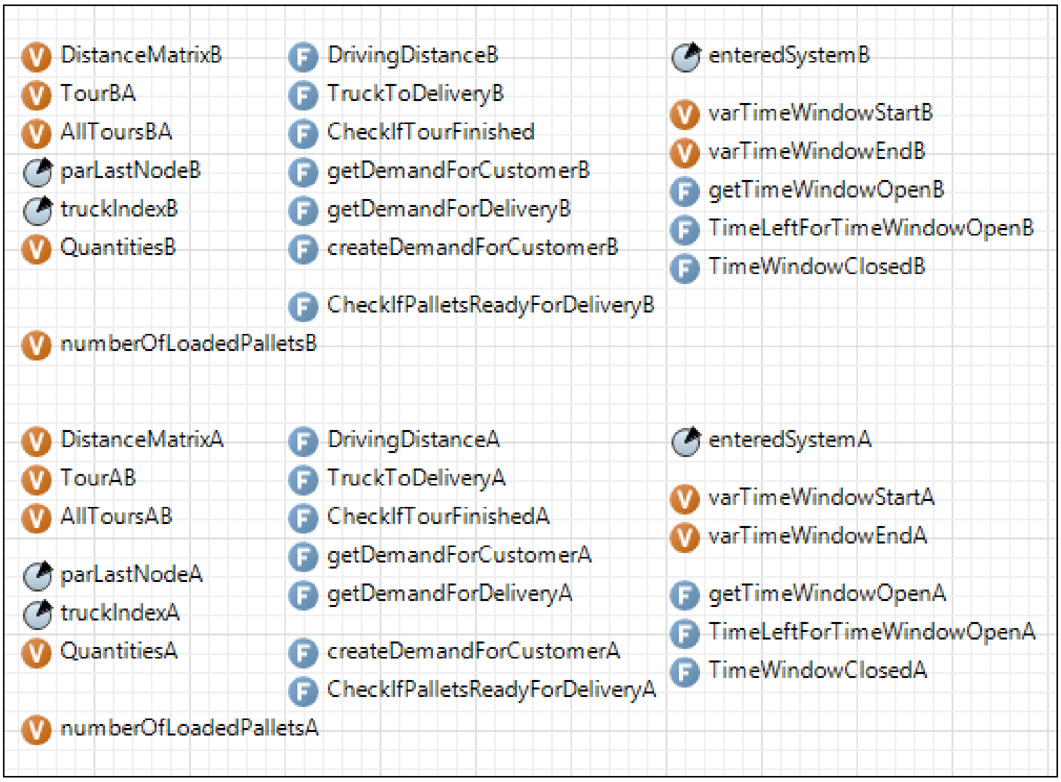

Figure 9: Functions and variables of Truck Agent to complete cluster tour

3.7.2.1. Functions of Truck Agent

The functions are needed to make the truck run through the given route. Major functions are highlighted like “createDemandForCustomerA/B” to create the total demand for each cluster. At each point where a delivery is completed, the system will check if the tour is finished or if a further customer has to be visited with “CheckIfTourFinshedA/B”; determining whether the truck will return back to the depot or drive immediately to the next customer. Once back at the depot, the truck drops off the load and checks again with a function if the tour has finished or if the truck needs to pick up goods for delivery “getDemandForDeliveryA/B”, and if so, the amount of goods it has to load “getDemandForDeliveryA/B” for the upcoming customers.

The set of TW functions is integrated to check each customer if a TW exists. In case of occurrence it is either open or closed, if it is open, the truck can continue and deliver the goods and if not, the function will compute the time the truck has to wait until the TW opens up again. In the worse case, the TW will be closed for the day and the truck is not able to deliver the goods and has to continue with its tour.

There are additional functions integrated at different levels to the model which command at its starting time to import the data out of the Excel file into Anylogic and save it into the assigned variables. These variables are integrated into the simulation model to access the same values and numbers of the FEAT-Team.

3.8. Experiment Parameters

To run the experiment and to obtain the desired output results, prime parameters of the variation level needed to be adjusted beforehand those are listed below. Every other parameter is changed within Excel and uploaded into the simulation model before the start.

For this project only, the parameter for the variation is used “varMINVariationDrivingTime” and “varMAXVariationDrivingTime” to produce the different levels of uncertainty.

One possible changeable parameter is for the vehicle to pick up goods to deliver to the train station. After testing various possibilities to get the correct amount of vehicles to deliver the goods in time, it is set to 10 vehicles. Additionally, an event function is monitored the stock level at the depot that all goods are “beamed” to the train station via vehicle. Otherwise goods will arrive at the train station with a delay, making it impossible to fulfill delivery at the other cluster.

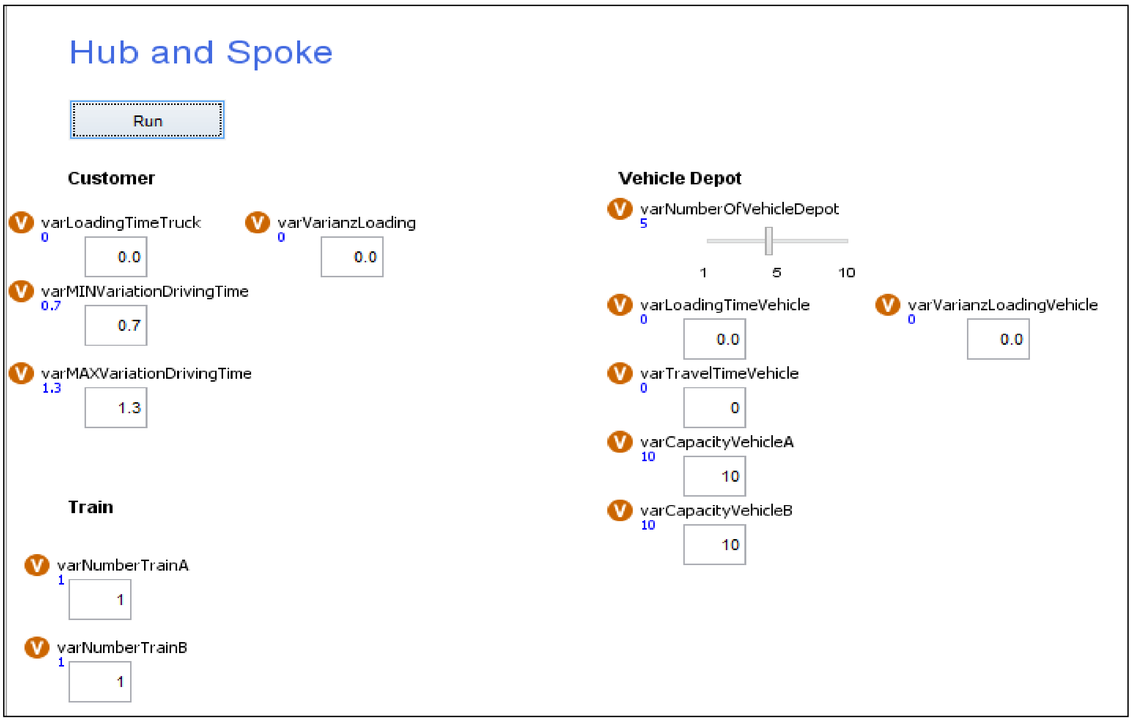

Figure 10: Parameter variation within Simulation run

Furthermore, the number of trains as well as the loading or travel time of the vehicle can be adjusted, should this perspective be included into the model.

3.9. Incorporation of Stochastics

The variation factor is implemented into the delay-function of driving time. The delay-function has a uniform distribution with a minimum and a maximum value, whereas the values change with the variation factor. The higher the uncertainty, the higher the variation factor, therefore becoming a wider spread. This parameter has the choice of values of the variation of 5, 10, 20, 25 and 30 percent.

To integrate stochastics into the model, the parameter of “parMINVariationDrivingTime” and “parMAXVariationDrivingTime” as mentioned in section 3.8 is implemented, together with the function of “DrivingDistanceA/B” of the truck agent. The “DrivingDistanceA/B” is a function to obtain the data from the distance matrix on Excel. In chapter 3.2 the implemented stochastics is described which are used in the model: a uniform distribution function. This function tool is provided by Anylogic together with many other distribution functions. In the delay objective of driving time the following uniform distributions with the different variation levels is integrated:

*“Uniform(parMINVariationDrivingTime*agent.DrivingDistanceA(), parMAXVariationDrivingTime*agent.DrivingDistanceA()”*

3.10. Applied Recourse Action to Original Tour

The decision of introducing recourse action to the original route of the FEAT-Team is the purpose of achieving feasible routes where the service level reaches a level of 100 percent. Recourse action is only applied when stochastics fluctuates the driving time of a truck so much that a delivery could not be fulfilled. For each of the three different recourse actions, the same procedure but with different actions involved is applied. The original tour was considered with all of the undelivered goods. The customers to whom a successful delivery could not be achieved, were taken out of the original route and placed into extra newly-created routes. The extra routes are in ascending order of the smallest TW of the customer first. That implies that the original tour received a smaller amount of customers and additional routes were created. This action should show that logistics are reallocated for the next day to complete the cluster of customers up to 100 percent. All of these three recourse actions are applied to one original tour if it not feasible; these actions are explained below.

3.10.1. Recourse Action I

The original tour with the outcome of the failure of the delivery was taken to build the new tour with the recourse action. Each of the non delivered goods were put into a single tour which started from the depot and drives directly to the customers, to whom delivery was unsuccessful, after which the truck returns back to the depot (0-1-0).
These single tours were created for such customers.

3.10.2. Recourse Action II

This action has the same characteristics as the one for recourse action I but supplementary to this, the truck received earlier starting times at the depot. The starting time varies and depends on the variation level. With low uncertainty, a lower time was chosen and for higher, corresponding additional time. The timing used for the variation level of 5 percent is 10 minutes, for 10 percent increased to 30 minutes and for 20, 25 and for a 30 percent variation level, the truck started 60 minutes earlier compare to the original time. The aim of earlier starting time at the depot is to get the advantage of gleaning more time to reach the given TW of a customer.

3.10.3. Recourse Action III

This action is different from the other two mentioned before because it involves the creation of just one extra tour, where all the customers are included to whom a delivery could not be achieved. When rescheduling the tour, all missed customers are integrated into the tour with an ascending order of TW as well as the application of the original assignment either the truck has a stopover at the depot or driving straight to the next customer is considered.

3.11. Total Travel Time

This topic is additionally invented to the problem set of the FEAT-Team. It looks beyond the cluster cost and the driving time of a route. The focus is on the actual time which a truck needs to return back to its base and complete a tour. This gives an overview of the waiting time in-between each time window, as well as the time a truck waits at the depot for receipt of the goods for delivery.

Since the research project has its main objective in allocating routes within the given restrictions in a timely manner, in this section the time which is not included into the cost of the deterministic solution is highlighted.

The objective is to find efficient solutions, while reducing waiting times, as well as reducing the truck fleet. In real world problems, transportation companies face the problem of optimizing their staffing cost, as well as of using the resources as efficiently as possible. It is presumed that labour costs have a high impact on total expenses to a company.

4. Results of Analysis

To obtain randomness within the variables of driving time, random seeds were chosen in the simulation model. To gain an estimate of the output data the mean of 10 independent replications for each data set was taken. Each replication has a length of 1440 minutes which represents a 24-hour day. This procedure, to observe performance measures was conducted in order to assess variability and gain feasible and decisive results. Anylogic was able to build the created model very quickly, within seven seconds, even with all the restrictions and agents involved.

To analyze the data from the simulation model, a comparison with the original data of the FEAT-Team was carried out. The difference between the two of them is presented in percentage form to gain a better comparison within the different problem sets and figures. All output data is collated in Excel and entered into a database to work with the Excel tool “Pivot table” to get satisfactory results in all kind of variations and from different viewpoints.

Different perspectives such as service level, cluster cost, sensitivity and travel time have been analyzed and the results are displayed with tables and figures, to be discussed later in this chapter.

4.1. Service Level Fulfillment

Out of the nine given data sets, seven had a completion rate of 100 percent in Service Level. This is obviously a good result given the probability to experience delays in delivery with a stochastic factor. Even though there could be longer driving time to a particular set of customers, the tour could be finished, whilst meeting customers’ expectations.

Only two data sets, with constraints of SuperTight TW for the 10 and 50 customers, did not reach the bench mark due to the stochastic in the model. These two data sets were separately adapted with recourse action, which is described in chapter 4.3.

4.2. Cluster Cost

The first area to look at is the cluster cost because the service level is completely fulfilled and for this reason, the main focus is on the influence of stochastic to the driving time of a tour. The aim is to analyze the behavior of cluster cost with the change of variation level to various restrictions as TW or the increase of customer requests. The table below contains the results of cluster costs for each of the seven data sets.

Average of Values2	Column Labels		
Row Labels	No TW	Super Tight	Tight TW
5.00%	**-12.34%**	**-0.21%**	**0.71%**
10.00	-7.92%	0.00%	2.92%
25.00	-13.27%	-0.43%	-0.14%
50.00	-15.82%		0.03%
10.00%	**-5.47%**	**0.00%**	**0.85%**
10.00	-7.43%	0.00%	2.91%
25.00	-12.96%	0.01%	-0.53%
50.00	3.96%	0.00%	0.16%
20.00%	**-11.03%**	**-0.09%**	**0.51%**
10.00	-7.19%	0.00%	2.77%
25.00	-11.83%	-0.26%	-0.73%
50.00	-14.06%	0.00%	-0.51%
25.00%	**-11.84%**	**0.16%**	**1.96%**
10.00	-8.57%	0.00%	5.40%
25.00	-11.95%	0.49%	0.45%
50.00	-15.00%	0.00%	0.02%
30.00%	**-11.54%**	**-0.25%**	**2.18%**
10.00	-5.65%	0.00%	4.49%
25.00	-12.81%	-0.74%	0.88%
50.00	-16.15%	0.00%	1.16%

Table 1: Cluster costs for all seven data sets without fulfillment gap

The differences in the constraint of TW are clearly visible on the figure below. No TW has mainly a negative and the Tight and SuperTight TW, on the contrary, have a positive impact on cluster cost.

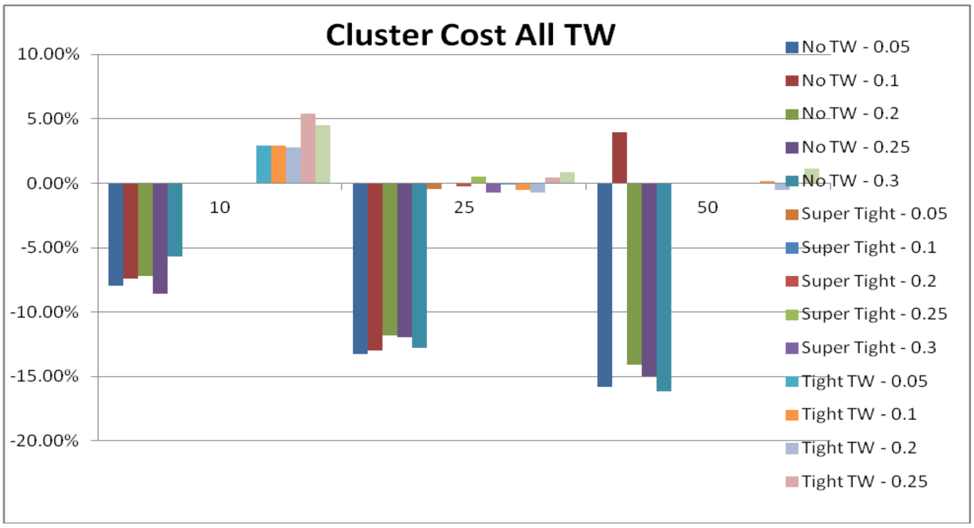

Figure 11: Cluster cost of all TW

For all customers, the constraint of No TW had a negative impact on cluster costs, except for one spike which is for 50 customers with a variation of 10 percent. Overall there is an increase of negativity in cluster cost with the increase of customers and variation of the variable for driving time. The range starts from 5.65 percent and goes up to 16.15 percent in change to the deterministic solution.

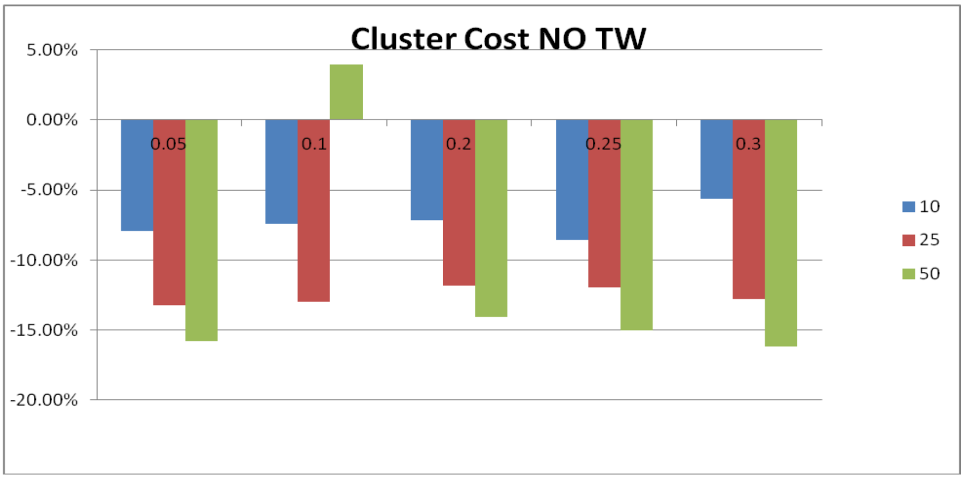

Figure 12: Cluster cost with restriction of NO TW

This may be the reason why the truck does not have to wait at time windows or the fact that the deterministic solution is calculated diffently. As the variation level increases, the driving time decreases correspondingly negatively and overall results in less cluster cost as the deterministic solution. Over the runs it accumulates up to a saving of up to 16 percent. This could be due to the fact that with many customers in one tour there is the posibility to save time with each customer. It shows that the stochastic model uses less driving time as the deterministic solution and for a real world problem this can be adopted as an opportunity to allocate less time for each tour and the result is hence, reduced costs.

Different figures shows the outcome of the Tight and SuperTight TW. There is a positive and negative change but remains close to the determenistic solution. The maximum is just above five percent. The graph shows the impact of smaller amount of customers to the cluster cost.

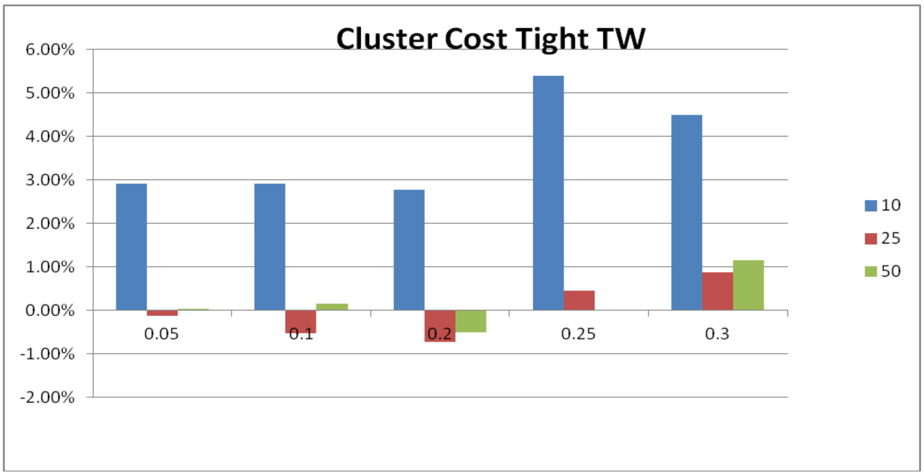

Figure 13: Cluster cost with restriction of Tight TW

The smallest difference compared to the original cluster cost is seen in the SuperTight TW, as the range is only up to minus 0.74 percent in this case.

The two different results of the constraint NO TW compared to the Tight TW gives a huge gap between the No TW and the Tight TW with only 10 customers which is presented in the following table.

	No TW			Super Tight			Tight TW		
Row Labels	**10.00**	**25.00**	**50.00**	**10.00**	**25.00**	**50.00**	**10.00**	**25.00**	**50.00**
5.00%	100.00%	100.00%	100.00%	0.00%	3.24%	0.00%	-36.89%	1.03%	-0.21%
10.00%	100.00%	100.00%	100.00%	0.00%	-0.06%	0.00%	-39.22%	4.11%	3.91%
20.00%	100.00%	100.00%	100.00%	0.00%	2.17%	0.00%	-38.48%	6.19%	3.64%
25.00%	100.00%	100.00%	100.00%	0.00%	-4.08%	0.00%	-62.96%	-3.78%	-0.11%
30.00%	100.00%	100.00%	100.00%	0.00%	5.77%	0.00%	-79.48%	-6.86%	-7.16%

Table 2: Comparison Cluster cost

This results from the fact that tours with No TW have negative cluster cost and the opposite is true with Tight TW. The reason for the difference in this special case comes may be due to the random choosen variables or from the calculation of the original determinic solution as mentioned before.

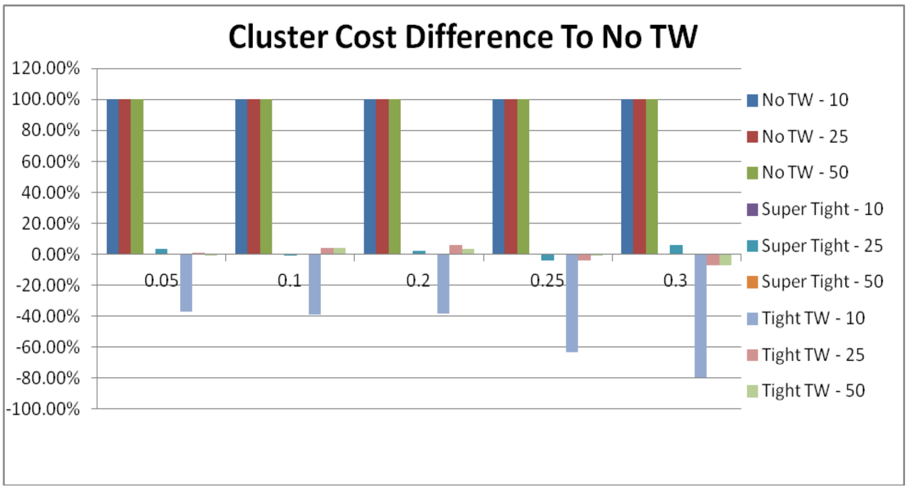

Figure 14: Comparison Cluster cost to NO TW

On this graph the gap is clearly visible as discribed before for the customer with 10 requests. The rest of the results have a minimum of change from one TW to another. This means that, as far as the total cluster cost is concerned, it is irrelevant if there is a TW involved or not.

Sensitivity

To examine the changes within the data, to highlight whether there is a correlation between the increase or decrease of cluster cost with the increase of variation, a sensitivity test was conducted. The output did, in fact, sense sensitivity to the variation coefficient. The coefficient of variation is calculated as follows: CV = SD/Mean*100 to get the percentage of the impact of the standard deviation to the mean.

Coefficient of Variation	*10*	*25*	*50*
No TW	-14.7961	-5.05012	-75.6543
Tight TW	32.01943	-4693.77	357.2738
Super Tight TW	450.69	-249.065	-13.84

Table 3: Sensitivity of variation factors

For example, the figures for all customers with Tight and SuperTight TW indicate no high standard deviation or mean but the coefficient indicates differently. The impact of the standard deviation to the mean is substantial: up to 4.600 percent. The first impression of the small range in change between 1.67 percent and 2.63 percent does not prove that there is no sensitivity. The slightly higher coefficient of the No TW with 50 request customers is due to the spike.

4.3. Recourse Action

The recourse action had to be taken everywhere that the service level could not be 100 percent fulfilled, as previously mentioned. The aim is to gain 100 percent service level integrating the different actions of new tour allocation. The original Tour used by the data of the FEAT Team and its outcome is labelled “MD Tour”. Only two data sets did not reach the bench mark and recourse action had to be applied. Both had a SuperTight TW one with the request for 10, and the other, for 50 customers.

To make a good approximation and gain representative data, five routes out of the 10 MD Tours were selected, and onto which recourse action was applied. Each new tour in the recourse action had 10 runs to get an average due to the stochastics. Again, out of these five tours the average was retained to get the final number for the applied recourse action. Overall, 50 runs were needed to complete one recourse action and to gain the result.

The general aspects of comparison are described as follows.

4.3.1. Service Level Fulfillment with Recourse Action

The first run from which the needed data for the recourse action is gleaned is called MD Tour. The figures show that with an increase in the variation level, a constant drop of service level is observable which had its maximum at 52.68 percent, which represents a high dropout quote. One of the explanatory reasons is that a truck could not deliver the goods in time because the train arrived late at the depot. Another is a higher variation to the variable and its randomness leads to more driving time and with the accumulation of total driving time, the given time window could not be reached in time, especially to the customers towards the end of a tour. Sometimes the time window was missed by just a matter of minutes.

The table includes data of the reached service level of all tours with the respective variation level as well as all applied recourse actions.

Row Labels	0.05	0.1	0.2	0.25	0.3
10					
MD Tour	-30.98%	-40.24%	-51.71%	-50.73%	-52.68%
Recourse I	-6.01%	6.29%	25.25%	21.49%	19.28%
Recourse II	-5.54%	2.86%	15.86%	16.14%	26.19%
Recourse III	-15.34%	-3.59%	4.14%	5.05%	18.56%
50					
MD Tour	-14.35%	-13.11%	-12.51%	-17.57%	-25.75%
Recourse I	1.36%	-4.29%	-17.78%	-19.31%	-2.33%
Recourse II	9.24%	-6.16%	-20.01%	-23.02%	-2.96%
Recourse III	10.87%	0.78%	-12.22%	-11.06%	-1.26%

Table 4: Reached Service Level with applied Recourse Action

The introduction of the recourse action did not give an achievement of complete fulfillment of the tour but in some cases the action does give rise to a better result.
The outcome of the recourse action is displayed in percentage form, which is the result of the difference with the MD Tour. The number was either positive or negative which indicates an impact to the service level of the tour: for example, if the figure is positive, it has a positive influence on the end result of completion. On the other hand, when it is negative, the fulfillment of the service level even got worse.

The diagram of service level fulfillment shows the different recourse actions with their success rate. Overall, for the cluster with 10 customers, the recourse actions have a positive impact on completion of service level. For example, if the recourse action II is considered, with plus 25.25 percent, the overall fulfillment of service is over 76 percent for this problem set. It must also be kept in mind that where there are a lower number of customers, each customer who is additionally satisfied will result in a bigger impact on the overall percentage.

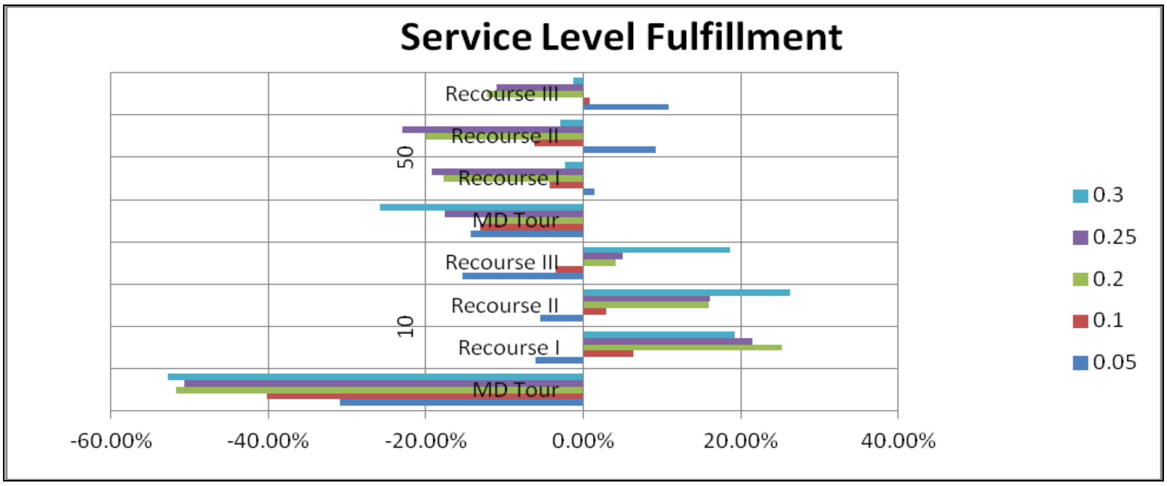

Figure 15: Service Level fulfillment with Recourse action

For the tour with 50 customers, however, it looks a slightly different. In this case, the MD Tour does not have such a high non-fulfillment service level at first, as was the case with the cluster with 10 customers. The recourse actions does not have an influence on increasing the service level, as only with a low variation of five percent, all three kinds of recourse actions made an improvement. One possible explanation for this is because there is less fluctuation in driving time and this leads to arriving closer to the deterministic driving times, meaning therefore that the time windows could be reached in time.

The comparison within the different recourse actions is discussed in chapters 4.3.3 and 4.3.4.

4.3.2. Cluster Cost with Recourse Action

The gained results of cluster cost for tours with recourse action are displayed in the table below. These cluster costs and those without recourse action, discussed in chapter 4.2, are very similar and very close to the original deterministic solution in the same category of SuperTight TW.

Row Labels	0.05	0.1	0.2	0.25	0.3
10	**-0.019518445**	**-0.010276866**	**-0.013338071**	**-0.001214876**	**-0.017949727**
MD Tour	0.10%	-0.41%	1.21%	-1.09%	1.34%
Recourse I	-0.67%	-0.41%	-1.21%	0.74%	-2.58%
Recourse II	-0.71%	-1.53%	-2.44%	0.24%	-2.68%
Recourse III	-6.53%	-1.76%	-2.88%	-0.38%	-3.26%
50	**0.01104228**	**0.00786545**	**-0.012775293**	**-0.010736272**	**0.012408398**
MD Tour	-4.77%	-4.82%	-4.30%	-4.19%	-5.87%
Recourse I	4.08%	3.35%	0.70%	1.05%	8.03%
Recourse II	3.93%	3.46%	-0.39%	1.02%	3.24%
Recourse III	1.17%	1.16%	-1.12%	-2.17%	-0.43%

Table 5: Cluster cost with Recourse action

It is observable that with the increase of variation level, the cluster costs correspond accordingly when considering the data of the cluster with 10 customers. The same phenomena could not be deduced with a higher amount of customers, as shown above.

Both of the above customers have the same characteristics in terms of reaching the greatest point at the highest variation level. The variation of cluster cost is negligible with respect to the original data.

Stochastics do not have a big impact on the cluster costs, as although small discrepancies are present among the variation levels, they do not make a considerable difference to the overall result.

4.3.3. Best Recourse Action

Ranking all three recourse actions into a top-ten order, the best and most efficient result is the recourse action I for the cluster of 10 customers, because it is placed within the top four on three separate occasions. It achieves its good results with the highest variation levels and through stochastic influence the service level could be increased by recourse action.

On the other hand, for a higher demand, a lower variation level influences the outcome of the recourse action. The result shows, that all three kinds of recourse action had a positive impact at a variation level of five percent.

Overall it can be said that for smaller amounts of goods, a single tour as recourse action has a better outcome then using one tour with all costumers. Conversely, the opposite applies for bigger cluster, where principally recourse action III had a better result and made a one tour action applicable.

Values	Total Service 10	Values	Total Service 50
Sum of Recourse II 30%	26.19%	Sum of Recourse III 5%	10.87%
Sum of Recourse I 20%	25.25%	Sum of Recourse II 5%	9.24%
Sum of Recourse I 25%	21.49%	Sum of Recourse I 5%	1.36%
Sum of Recourse I 30%	19.28%	Sum of Recourse III 10%	0.78%
Sum of Recourse III 30%	18.56%	Sum of Recourse III 30%	-1.26%
Sum of Recourse II 25%	16.14%	Sum of Recourse I 30%	-2.33%
Sum of Recourse II 20%	15.86%	Sum of Recourse II 30%	-2.96%
Sum of Recourse I 10%	6.29%	Sum of Recourse I 10%	-4.29%
Sum of Recourse III 25%	5.05%	Sum of Recourse II 10%	-6.16%
Sum of Recourse III 20%	4.14%	Sum of Recourse III 25%	-11.06%

Table 6: Best results with Recourse action for Cluster with 10 and 50 Customers

4.3.4. Comparison Recourse Action I and II

Both recourse actions consist of single routes. It must be made clear, for both actions but most likely for the cluster with 50 customers, the more customers cannot be serviced initially on the MD Tour as more trucks were needed to plan the recourse action. The model was designed with a FIFO queuing system at the depot which can disrupt the original tour, because the truck from the original tour had to wait until all recourse trucks are loaded and had left the depot. The result of this disturbance led to the truck from the original tour not being able to deliver its goods punctually, namely before the time window of the customers closed.

As the problem set with 10 customers indicates, there are less recourse routes beforehand and the truck from the original tour did not have to wait particularly long at the depot before continuing with its tour. Therefore, the recourse action for the cluster with 10 customers gleans overall a better result than the one for 50 customers.
Particularly noteworthy is that there is a positive increase in service level for the 10 customers conducting the recourse action for almost all variation levels. Recourse action I has a better impact with the increment of variation. The recourse action II has

the best result, with its greatest influence on completion rate of service level at the highest variation level and outperformed recourse action I.

The table below shows the details of the FIFO procedure quite well.

Values	Total Service 10	Difference	Values	Total Service 50	Difference
Min of Recourse II 5%	-5.54%		Sum of Recourse I 5%	1.36%	
Sum of Recourse I 5%	-6.01%	-0.47%	Sum of Recourse II 5%	9.24%	7.88%
Sum of Recourse I 10%	6.29%		Sum of Recourse I 10%	-4.29%	
Sum of Recourse II 10%	2.86%	-3.43%	Sum of Recourse II 10%	-6.16%	-1.87%
Sum of Recourse I 20%	25.25%		Sum of Recourse I 20%	-17.78%	
Sum of Recourse II 20%	15.86%	-9.39%	Sum of Recourse II 20%	-20.01%	-2.23%
Sum of Recourse I 25%	21.49%		Sum of Recourse I 25%	-19.31%	
Sum of Recourse II 25%	16.14%	-5.35%	Sum of Recourse II 25%	-23.02%	-3.71%
Sum of Recourse I 30%	19.28%		Sum of Recourse I 30%	-2.33%	
Sum of Recourse II 30%	26.19%	6.91%	Sum of Recourse II 30%	-2.96%	-0.63%

Table 7: Comparison Recourse action I and II

Conversely, the results of the 50 customers show the opposite to be true. The lowest variation level had the greatest impact with an increase of 9.24 percent with the recourse action II. In the other cases, however, recourse action I was better than II, even though it did not have a globally positive impact on enhancement of the service level.

4.3.5. Sensitivity of Recourse Action

The tables below indicate sensitivity to variation within all recourse actions. For example, the recourse action III has a high negative impact on cluster cost as well as service level for the cluster with 50 customers. All other results represent an influence of the mean due to variation of probability in the variable driving time.

Coefficient of variation Cluster Cost	10	50
Recourse I	-146.66	85.57
Recourse II	-85.24	82.28
Recourse III	-77.27	-522.05

Table 8: Sensitivity of Cluster cost

Coefficient of variation Service Level	10	50
MD Tour	-20.83	-32.69
Recourse I	97.43	-111.39
Recourse II	112.18	-153.54
Recourse III	705.50	-367.54

Table 9: Sensitivity of Service Level

With the exception of the MD Tour in spite of service level it does have an indicator of sensitivity. Overall, it illustrates with change of variation level, the output of data gets influenced by stochastics.

4.4. Total Travel Time

Travel time was not included in the original research project but it is nevertheless an important point to consider when planning routes. The total travel time of the truck until it returns back at the depot includes all waiting times, e.g. at the depot to get the delivery or at the TW of the customer itself. Waiting time is expensive due to the fact that labor cost increases. For a company, these expenses need to be included into calculations because of surplus accounting. Any entrepreneur has to consider these costs into the planning schedule otherwise resources are unused.

Due to the fact that the cluster time includes only the driving time of a truck from the depot to its customer and back, the discrepancy must be extremely high. This was confirmed by the results presented in next two sections: one for the complete fulfilled service level and the other one for the travel time by recourse action.

4.4.1. Travel Time with fulfilled Service Level

In both cases of NO TW and Tight TW, the travel time either hits the 1,000 percent mark or is extremely close to it, which is a massive discrepancy vis-à-vis the cluster cost.

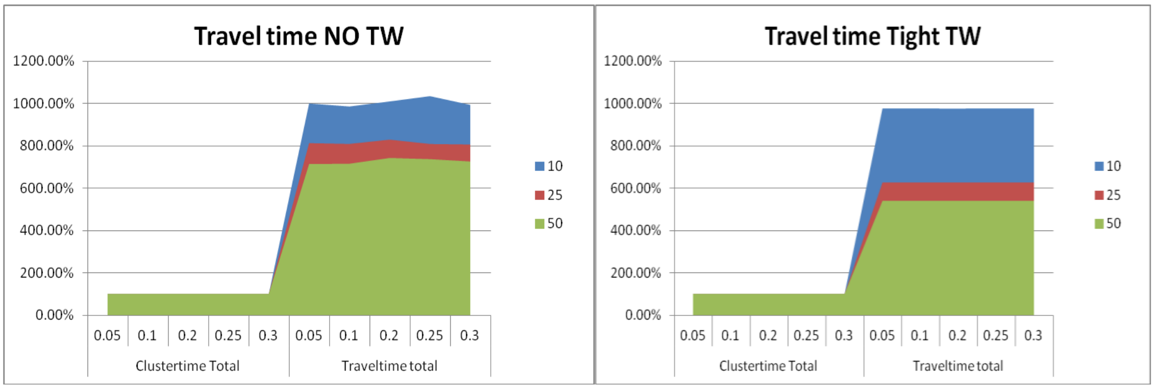

Figure 16: Overview Travel time with NO TW and Tight TW restriction

With NO TW the truck does not have to wait at any TW and for this reason it shows fluctuation with the different variation levels. The routes for the Tight TW have stable results, because with the various TW, the results level each other out. On the graph it is visible that with the restriction of Tight TW the travel time drops with the increase of customer requests.

To compare both results with No TW, there is a higher waiting time at the depot because this is the only waiting time that exists for such a route. Once TWs are involved, the waiting time at the depot decreases because the truck drives efficiently between the different TW slots and as a result, the overall waiting time is reduced.

In summary, the result from analyzing the travel time compared to the cluster costs is that a tour has extremely high waiting times which are not included into the cost of the deterministic solution.

4.4.2. Travel Time with Recourse Action

As described in the previous chapter concerning the recourse action and how they were implemented (especially for the recourse action I and II), there are more trucks needed to complete the requests, which implies overall greater travel time. The outcome is astonishing because the increase was up to 1,600 percent more than the cluster cost.

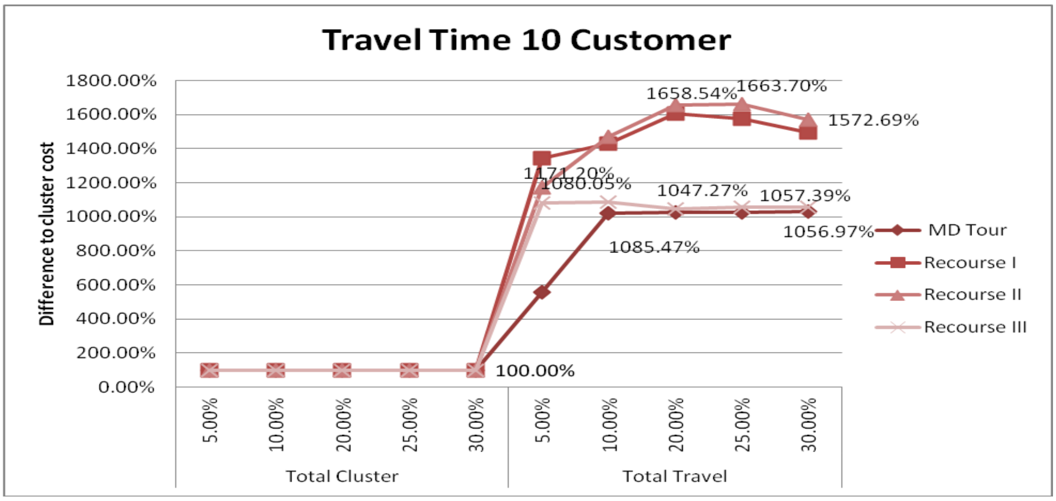

Figure 17: Travel time compare with cluster cost with 10 customers

Primarily responsible for the increase in travel time, within the problem-set SuperTight TW and 10 customers, was the recourse action II which has its peak at 25 percent variation level. The best result with constantly stable results in travel time is the MD tour and recourse action III.

A different result on the other hand, is the result of the problem-set of the 50 customer requests. Here the recourse action III has the best result and drops with the rise of variation. Once again the recourse action II comes out on top because the tour contains the travel time plus the extra time through starting earlier, even though the MD Tour does top the recourse action II at one particular point. It appears that as the number of customers' increases, so too does the efficiency of the tour. The maximum of 1,070 percent for this problem is not as dramatic as the travel time for the cluster of 10 customers.

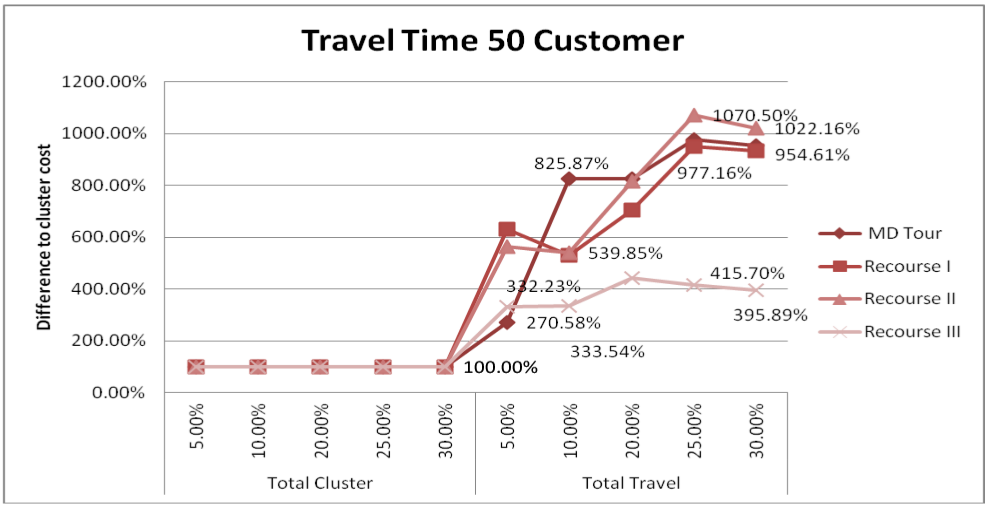

Figure 18: Travel time compare with cluster cost with 50 customers

This result is more trustworthy than that for the 10 customers, because the low amount of requests leads to a bigger impact on the average of changes.

A desirable result noticed is, that with the SuperTight TW the travel time within the recourse action III is around 400 percent, even though that one more truck than with the original tour is required. It must be borne in mind that with the additional waiting time of one truck, this still leads to overall good travel time. The truck drives efficiently within the given time windows and depot spots and thus reduces waiting time. It is a very good result and could be considered for a recourse action to reduce travel time and overall cost.

4.5. Summary

The outcome using deterministic data with a stochastic simulation model is surprisingly good. Seven out of nine data sets could be completed with a fulfilled service level which is a feasibility of 77.78 percent. Feasible routes are the main goal in logistical problems while keeping costs at a minimum. The cluster cost had a higher variation due to the range in the variable driving time with no TW compared to the one with a Tight or SuperTight TW. An increase could be observed when increasing variation. The overall cluster cost for Tight and SuperTight TW do not differ very much from the original data which was also observed for the cluster cost of the tours with recourse action.

For all nine data sets, there is sensitivity in cluster cost and service level regarding the variation level of the stochastic variable driving time highlighted by the coefficient of variation with its results.

The service level of the unfulfilled delivery, using recourse action, is very low and has a huge drop-out quote. With SuperTight TWs and stochastic, the truck was not able to complete 50 percent of its tour to a satisfactory level. Even when the routes were reconstructed with recourse action, the service level could not reach 100 percent and be deemed not feasible.

The positive outcome of the recourse action depended on the amount of customers. In this study the lower amount of customers had a better impact on service level with the recourse action I than the one with more customers. The starting time of a truck did not have the affect of reaching the TW in time, which shows the result of the recourse action II. This can be explained by the waiting time at the depot and time windows of previous customers before reaching the critical time windows. The best result for the 10 customers was a service level completed up to 76 percent.

With a bigger cluster of 50 customers, the last recourse action III had its best outcome with a maximum of almost 11 percent increment. Overall the influence of the recourse action III was only limited to the service level. Only with a smallest variation level of five percent, the recourse action had a positive impact on the completion of service level.

The last area considered was the travel time of a tour. The result represents the waiting time of a truck while the TW is closed with the train failing to arrive at the depot. The travel time without recourse action was, as expected, less than those with recourse action, as more trucks were needed which increases the overall waiting time. The tours with 10 customers had the most waiting time with No TW with up to 1,000 percent higher than the cluster cost. With constrains of TW, the waiting time dropped with higher amounts of customers down to 500 percent above the cluster cost.

The recourse action II had a poor influence on the travel time with a maximum of 1,600 percent with 10 customers above the deterministic cluster cost. The best recourse action in terms of travel time is number III which reduces overall waiting time through efficiency with the constraint of SuperTight TW. Introducing a single tour to serve all customers with SuperTight TW gives a better result through the completion of service level as well as the reduction of waiting time.

5. Conclusion

In this section, a short summary of the master thesis research question and its outcome is presented, as well as an outlook into further possibilities using the simulation model which has been created.

5.1. Reflection of the Study

The simulation model was created to build a deterministic problem with its optimal solution into a stochastic environment with all its restrictions and given data by the FEAT-Team, to come closely to the deterministic solution. The objective of the master thesis is to analyze the behavior of deterministic routes with integrated stochastics and to check their feasibility.

The results gained were not particularly surprising and differ from the deterministic solutions. Stochastics has an influence on the feasibility of routes, but not on all restrictions and problem sets. It has an impact in cases of very narrow time windows (SuperTightTW) and time differences caused by uncertainty rendering a delivery not possible.
The analysis of sensibility to the variation factor illustrates a correlation between the factor and the service level, as well cluster cost.

Overall, the service level decreases with an increase of requests and uncertainty which was expected in a real world problem because it makes it more difficult to predict negative externalities. This has an influence on the costs which increase with uncertainty.
Unfortunately, the implemented recourse action did not achieve feasibility but in certain areas does, however, ensure a better result.

The outcome of waiting time up to 1,600 percent is extremely high and has to be considered by logistics companies when reallocating routes. Moreover, a closer investigation of the topic with time windows of customers in general was required. It is difficult to include time windows into a route without increasing waiting time which comes automatically as soon as time windows become too narrow.

For this master thesis it was reasonable to consider stochastics because first it is a rare tool to use and secondly, with these results an influence could be observed as could the level to which this was the case.

5.2. Model possibilities

The simulation model is not limited to this specific research project, and can do much more. The whole model can be applied to a real world problem, for example, for transportation company which faces different areas of constrains. The model integrated more variables and separated areas of a logistics like depot, a dispatch at the depot to the long haul with vehicles and a truck fleet for the routes to serve the customers.
Through the different variables integrated in the cycle of delivery to the train station, driving time for example can be adjusted if the depot is not located next to the train station. Another variable is the loading time to load or unload the vehicle in different areas can be varied going to and coming from the train station. There are many more variables which can also be adapted.

The depot was created to include all needed information of unloading goods, storage capacity, work flow within the depot and loading of trucks to display the outcome of a real world depot.

The model can be expanded to more than two clusters of customers, mainly for companies that have several clusters to deal with. A truck break down can also be included into the model to integrate another stochastic influence which naturally cannot be planned in advance.

In summary, the model can be useful to look beyond the deterministic calculation. Given the fact that not many companies use stochastic tools for their planning, this could be helpful to have an even better understanding of possible uncertainty and to assist in planning ahead for future investments.

Bibliography

Andersen, J., & Christiansen, M. (2009). Designing new European rail freight services. *Operational Research Society Ltd* , 348-360.

Borshchev, A. (2013). *The Big Book of Simulation Modeling; Multimethod Modeling with AnyLogic 6.* North America: AnyLogic.

Caris, A., Macharis, C., & Janssens, G. K. (2012). Corridor network design in hinterland transportation systems. *Flexible Services and Manufacturing Journal* , 294-319.

Caris, A., Macharis, C., & Janssens, G. K. (2013). Decision support in intermodal transport: A new research agenda. *Computers in Industry* , 105-112.

Caris, A., Macharis, C., & Janssens, G. K. (2008). Planning Problems in Intermodal Freight Transport: Accomplishments and Prospects. *Transportation Planning and Technology* , 277-302.

Chang, T.-S. (2007). Best routes selection in international intermodal networks. *Computers & Operations Research* , 2877 – 2891.

Crainic, T. G., & Laporte, G. (1997). Planning models for freight transportation. *European Journal of Operational Research* , 409-438.

Demeyer, S., Audenaert, P., Pickavet, M., & Demeester, P. (2013). Dynamic and stochastic routing for multimodal transportation systems. *The Institution of Engineering and Technology* , 112-123.

Dragomir, A., Nicola, D., Soriano, A., & Gansterer, M. (2017). Multi-depot pickup and delivery problems in multiple regions: A typology and integrated model. Working paper. University Vienna.

Dube, P., Goncalves, J. P., Mahatma, S., Barahona, F., Naphade, M., & Bedeman, M. (2014). Simulation Based Analytics for Efficient Planning and Management in Multimodal Freight Transportation Industry. *Simulation Conference Winter 2014* , 1943-1950.

Grigoryev, I. (2015). *Anylogicz in three days.* Marston Gate: Amazon.co.uk, Ltd.
Hamzaoui, S., & Ben-Ayed, O. (2011). Parcel distribution timetabling problem. *Oper Manag Res* , 138-149.

Huang, M., Hu, X., & Zhang, L. (2011). A decision method for disruption management problem in intermodal freight transport. *Intelligent Decision Technologies 10* , 13-21.
Ishfaq, R., & Sox, C. R. (2012). Design of intermodal logistics networks with hub delays. *European Journal of Operational Research* , 629-641.

Lin, C.-C., & Chen, S.-H. (2001). The hierarchical network design problem for time-definite express common carriers. *Transportation Research Part B* , 271-283.

Macharis, C., & Bontekoning, Y. (2003). Opportunities for OR in intermodal freight transport research: A review. *ScienceDirect, European Journal of Operational Research* , 400-416.

Maia, L. C., & Couto, A. F. (2013). An innovative freight traffic assignment model for multimodal networks. *Computers in Industry* , 121-127.

Martins, P. A. (29. 06 2015). *Supermarket Sizing in Production Flow Systems Based On Lean Principles.* Visit homepage 15. 04 2017 at https://sigarra.up.pt/feup/pt/pub_geral.show_file?pi_gdoc_id=419073

Meng, M., Shao, C. F., Wong, Y. D., & Zhang, J. (2014). Multimodal Network Equilibrium with Stochastic Travel Times. *Hindawi Publishing Corporation* , 1-8.

Miller-Hooks, E., Zhang, X., & Faturechi, R. (2012). Measuring and maximizing resilience of freight transportation networks. *Computers & Operations Research* , 1633-1643.

Nozick, L. K., & Morlok, E. K. (1997). A model for medium-term operations planning in an intermodal rail-truck service. *Transportation Research Part A, 31(2)* , 91-107.

Sid'Ahmed, O. K. (2009). *Illustrated glossary for transport statistics.* ISBN: 978-92-79-17082-9: UNECE.

Sitek, P., & Wikarek, J. (2012). Optimization Model for Multimodal Transportation Networks Based on Supply Chain. *Foundations of Management* , 77-96.

SteadieSeifi, M., Dellaert, N. P., Nuijten, W., Van Woensel, T., & Raoufi, R. (2013). Multimodal freight transportation planning: A literature review. *European Journal of Operational Research* , 1-15.

Tsamboulas, D., Vrenken, H., & Lekka, A.-M. (2007). Assessment of a transport policy potential for intermodal mode shift on a European scale. *ScienceDirect, Transportation Research Part A* , 715-733.

Woxenius, J. (2007). Generic Framework for Transport Network Designs: Applications and Treatment in Intermodal Freight Transport Literature. *Transport Reviews* , 733-749.
Ziliaskopoulos, A., & Wardell, W. (2000). An intermodal optimum path algorithm for multimodal networks with dynamic arc travel times and switching delays. *European Journal of Operational Research* , 486-502.

Ziliaskopoulos, A., & Wardell, W. (2000). An intermodal optimum path algorithm for multimodal networks with dynamic arc travel times and switching delays. *European Journal of Operational Research* , 486-502.

Appendix A. Abstract

The main objective for this master thesis is to create a simulation model for a Hub-and-spoke transportation problem, or more precisely, for a two cluster with multi-depot network transportation problem. The simulation model is based on the data from the FEAT-Team and their deterministic solution. Their developed deterministic model was successfully transferred to a stochastic model including full integration of restrictions and data from the FEAT-Team. Therefore, the optimal solutions, coming from the deterministic model, were analyzed and compared in a stochastic environment.

The problem sets of the research team contain different cluster sizes of customers to whom should be delivered, as well as different time window restrictions. Additionally, more restrictions to a logistic problem were applied to problem sets.

The main objective of this thesis is to observe if there is a change in service level or cluster cost to the deterministic optimal solution routes and additionally, to which extent this is the case.

The simulation model was created with Anylogic 7 University Edition with the help of the Big Book of Simulation Modeling and some YouTube videos.

The results of cluster cost, service level and travel time were analyzed compared to the deterministic solution. Highlights were reported, the sensitivity of the variation level of stochastics considered, as well as the outcome of the recourse action applied. Two main findings of this study were on the one hand that 77.78 percent of all routes reached the service level to the fullest and on the other hand that recourse action did not have any influence on feasibility of the service level.

Appendix B. Zusammenfassung

Das Hauptziel dieser Masterarbeit liegt darin ein Simulationsmodel für ein Transportproblem mit speichenförmiger Anordnung zu einer zentralen Anlaufstelle (Hub-and-spoke Logistik) zur Unterstützung des Universitären Forschungsteam FEAT-Team zu entwickeln. Das Model entwickelte sich zu einem spezielleren Netzwerk, dessen dem Logistikaufbau mit zwei Clustern und mehreren Lagern entspricht. Es ist möglich sämtliche deterministischen Daten vom Forschungsteam und deren verbundenen Restriktionen in die Simulation einzuspeisen und zu verarbeiten. Es wurden Analysen der Veränderungen, die durch die Implementierung von Wahrscheinlichkeitsverteilungen verursacht wurden, durchgeführt.

Die einzelnen Problemstellungen die vom Forschungsteam vorgegeben wurden, beinhalten unterschiedliche Größen von Kunden die beliefert werden sollten sowie unterschiedliche Zeitfenster in denen die Kunden angeliefert werden konnten. Weitere zusätzliche Angaben zur Erstellung der logistischen Problemstellung wurden vom FEAT Team vorgegeben und integriert.
Das Ziel der Arbeit ist es, Unterschiede zur determistischen Lösung aufzuzeigen sowie dessen Ausmaß festzustellen, um diese für operative Entscheidungen bei Zukunftsplannungen zu nutzen.

Das Simulationsmodell wurde mit dem Programm Anylogic 7 University und mit Hilfe von dessen entwickelten Buch „Big Books of Simulation Modeling“ erstellt. Weiteres dienten Youtube Videos zur Unterstützung- und zu Veranschaulichungszwecken.

Die Ergebnisse von Clusterkosten, Service Level und Fahrzeiten wurden mit der deterministischen Lösung verglichen und große Abweichungen und Veränderungen aufgezeigt. Ebenso wurde eine Sensibilitätsanalyse in den unterschiedlichen Variationen von Schwankungen, die für die Wahrscheinlichkeitsverteilung verwendet wurden, duchgeführt. Die implementierte „Recourse Action“ wurde auf ihre Umsetzbarkeit geprüft und dokumentiert. Daraus wurden zwei Haupterkenntnisse gewonnen. Zum einen haben 77,78 Prozent aller Routen den Service Level zu 100 Prozent erreicht und zum anderen konnte kein positiver Effekt der Recourse Action auf den Service Level festgestellt werden.

Appendix C. Process Modeling Library

As per Anylogic: The agents contained in the Process Modeling Library are the building blocks used to construct the flowcharts. As usual, there are objects that generate agents, control agent flow, process agents, work with resources, and transport agents. In this reference guide, they are described in the following categories:

Source	Generates agents.
Sink	Disposes incoming agents.
Delay	Delays agents by the specified delay time.
Queue	Stores agents in the specified order.
SelectOutput	Forwards the agent to one of the output ports depending on the condition.
SelectOutput5	Routes the incoming agents to one of the five output ports depending on (probabilistic or deterministic) conditions.
Hold	Blocks/unblocks the agent flow.
Match	Finds a match between two agents from different inputs, then outputs them.
Split	For each incoming agent ("original") creates one or several other agents-copies.
Combine	Waits for two agents, then produces a new agent from them.
Assembler	Assembles a certain number of agents from several sources (5 or less) into a single agent.
MoveTo	Moves an agent from its current location to new location.
Conveyor	Moves agents at a certain speed, preserving order and space between them.

ResourcePool	Provides resource units that are seized and released by agents.
Seize	Seizes the number of units of the specified resource required by the agent.
Release	Releases resource units previously seized by the agent.
Service	Seizes resource units for the agent, delays it, and releases the seized units.
ResourceSendTo	Sends a set of portable and/or moving resources to specified location.
ResourceTaskStart	Defines the start of the flowchart branch modeling the task process for resource units (usually it is a resource preparation process).
ResourceTaskEnd	Defines the end of the flowchart branch modeling the task process for resource unit(s) (usually it is a wrap-up process).
ResourceTask	Defines some custom task for resources that cannot be defined using the provided standard patterns for failures, maintenance, breaks.
Enter	Inserts agents created elsewhere into the flowchart.
Exit	Accepts incoming agents.
Batch	Accumulates agents, then outputs them contained in a new agent.
Unbatch	Extracts all agents contained in the incoming agent and outputs them.
Dropoff	Extracts the selected agents from the contents of the incoming agent.
Pickup	Adds the selected agents to the contents of the incoming agent.
RestrictedAreaStart	Limits number of agents in a part of flowchart between corresponding area start and area end blocks.
RestrictedAreaEnd	Ends an area started with RestrictedAreaStart block.
TimeMeasureStart	**TimeMeasureStart** as well as TimeMeasureEnd compose a pair of objects measuring the time the agents spend between them, such as "time in system", "length of stay", etc. This object remembers the time when an agent goes through.
TimeMeasureEnd	**TimeMeasureEnd** as well as TimeMeasureStart compose a pair of objects measuring the time the agents spend between them. For each incoming agent this object measures the time it spent since it has been through one of the corresponding TimeMeasureStart objects.
ResourceAttach	Attaches a set of portable and/or moving resources to the agent.
ResourceDetach	Detaches previously attached resources from the agent.

Modeling warehouses and storages

RackSystem	Models a storage zone containing a set of racks (defined by PalletRack shapes), providing centralized access and managing of racks.
RackPick	Picks an agent from a cell of a rack (PalletRack) or a storage zone (RackSystem) and moves it into the specified network node.
RackStore	Places an agent into a cell of the specified rack (PalletRack) or storage zone (RackSystem).

Auxiliary

PML_Settings	Defines some auxiliary settings either related to all library blocks or configuring the behavior of some blocks.
Wait	This block is like **Queue** block with one exception: it supports manual retrieval (you need to call `free()`, or `freeAll()`. It has no ordering (except the case when preemption occurs, if the latter is turned on).
SelectOutputIn	Both with **SelectOutputOut** acts as two halves of large multi-exit **SelectOutput** block.
SelectOutputOut	Both with **SelectOutputIn** acts as two halves of large multi-exit **SelectOutput** block.
PlainTransfer	A place to write some action when agent passes through some point of your flowchart.