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Electric Vehicle Routing Problems:
The operations of electric towing trucks at an airport under uncertain arrivals and departures

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Abstract

As a result of the Paris Agreement, electric taxiing of aircraft needs to be the standard and all ground-based activities at a Dutch airport need to be zero-emission by 2030. This requires an energy-transition at airports, where decision-makers need to decide which type of Ground Service Equipment (GSE) needs to be bought in order to meet the Paris Agreements. In this thesis, we developed **3 mathematical models** that describe the **operations of electric towing trucks** that perform the taxi procedure. Firstly, **a deterministic Electric Vehicle Routing Problem (EVRP)** is developed as a Mixed Integer Linear Program (MILP) that determines the operations of electric towing trucks for deterministic arrival and departure times of the aircraft, minimizing the electricity costs. These electric towing trucks tow aircraft from the landing lane (gate) to the gate (runway) within a time-window and the trucks need to charge at a charging station when their battery is empty.

As the uncertainty in arrival and departure times of aircraft has an impact on the operations of the electric towing trucks, decision-makers need to know what the effect on the operations of electric towing trucks is. So, the second model that is developed is an EVRP with uncertain arrival and departure times described by a **Robust Optimization (RO)-program**. This RO-based program schedules the electric trucks at the beginning of the day, minimizing the electricity costs, while ensuring aircraft from a large number of sampled scenarios are towed on time, whilst the arrival/departure times are uncertain.

Thirdly, a **dynamic EVRP** with uncertain arrival and departure times of aircraft is developed to determine the optimal operations throughout the day using the information about the actual arrival and departure times that becomes available throughout the day. This **Stochastic Sequential Decision Problem (SSDP)** is solved by a **Dynamic Approximated Cost Algorithm (DACA)**.

The **results of the deterministic model** show that the computational complexity of an EVRP increases significantly compared to a Vehicle Routing Problem (VRP) of non-electric trucks due to the decision variables (DVs) associated with the charging of the trucks. Compared to a VRP of non-electric trucks, the EVRP of electric towing trucks of our formulation consists of 8 times more binary decision variables and the number of non-zero elements of the constraint matrix of the MILP is about 4 times larger.

The **RO-based EVRP** is found to be of the same order of computational complexity as the deterministic EVRP. As trucks are scheduled to be occupied longer with a tow job of an aircraft, compared to the deterministic model, this results in more trucks needed to tow all aircraft.

Results of the EVRP with uncertain arrival and departure times described as a **SSDP**, show that fewer trucks may be needed to serve all aircraft, compared to the RO-based EVRP. However, the computational complexity of the SSDP is significantly higher compared to the deterministic and RO-based model, so the SSDP is only suitable to determine the operation of a relatively small flight schedule and a small fleet of trucks within reasonable computation time.

Contents

Nomenclature

$\mathcal{A}_p$	Set of actions that can be chosen from at decision epoch p *
a_p	Action chosen at decision epoch p *
a_p^π	Action chosen from policy π *
c	Index, $c \in C_c$
c_k^t	Truck category of truck k
c_i^r	Request category of request i
C_c	Set of costs of charging speeds
$\mathcal{C}_c$	Capacity of truck
$\mathcal{C}_s$	Set of charging speeds
C_p	Direct costs at decision epoch p *
C^a	Post-decision total electricity costs *
$d_{i_{c_j}}$	Action of going to the i^{th} depot to charge with the charging speed of option j *
D	Set of depots
e_i	Earliest moment request i may be towed
γ	Discount factor *
h_i	Status of request i (handled, assigned or not yet assigned) *
h_i^a	Post-decision status of request i *
i	Index, $i \in I \cup D$
I	Set of requests
j	Index, $j \in I \cup D$
k	Index, $k \in K$
K	Set of trucks
$\mathcal{K}_p$	Set of truck that a decision needs to be made for at decision epoch p *
$l_i^{a,d,e}$	Destination location of arriving/departing aircraft of request i
$l_i^{a,d,s}$	Start location of arriving/departing aircraft of request i
l_i	Latest time request i may be towed
l_k	Location of truck k *
l_k^a	Post-decision location of truck k *
p	Decision epoch *
P	Final decision epoch *
π	Policy *
π^*	Optimal policy *
Π	Set of possible policies *

Table 1: * Elements only appear in Chap. 5 on Stochastic Sequential Decision Problems.

q_i	Decision variable battery level at start of request i
$q_{i,j,k}$	Electricity used when $x_{i,j,k} = 1$
q_k	Electricity level of truck k *
q_k^a	Post-decision electricity level of truck k *
s_i	Decision variable starting time of tow
S_p	State at decision epoch p *
S_P	Absorbing state *
S_p^a	Post-decision state *
t_k	Moment in time truck k is finished with its current tow *
t_k^a	Post-decision time truck k is finished with its current tow *
$t_i^{a,d}$	Arrival/departure time of request i
t_i	Decision variable amount of time charged
$t_{i,j,k}$	Time duration corresponding to $x_{i,j,k} = 1$
T_p	Time of decision epoch p *
$\tilde{t}_i^n$	n^{th} sampled arrival time of request i
$\tilde{t}_i^{\max}$	Maximum of the sampled arrival times of request i
$\tilde{t}_i^{\text{mean}}$	Mean of the sampled arrival times of request i
V_t	Value function at time t *
W_p	Exogenous information that became known between decision epochs $p-1$ and p *
$\mathcal{W}_p$	All available exogenous information at decision epoch p *
$x_{i,j,k}$	Binary decision variable, consecutive handling of requests

Table 2: * Elements only appear in Chap. 5 on Stochastic Sequential Decision Problems.

Abbreviations

ADP Approximate Dynamic Programming.

APU Auxiliary Power Unit.

CO_2 Carbon-dioxide.

CSO Civil Society Organizations.

DACA Dynamic Approximated Cost Algorithm.

DV Decision Variable.

EVRP Electric Vehicle Routing Problem.

FPU Fixed Power Unit.

GHG Green House Gasses.

GPU Ground Power Unit.

GSE Ground Service Equipment.

GSH Ground Service Handlers.

ICAO International Civil Aviation Organization.

LIFO Last In, First Out.

LP Linear Program.

MILP Mixed Integer Linear Program.

RO Robust Optimization.

SP Stochastic Program.

SSDM Stochastic Sequential Decision Model.

SSDP Stochastic Sequential Decision Problem.

VRP Vehicle Routing Problem.

VRPPD Vehicle Routing Problem with Pick-up and Delivery.

VRPTW Vehicle Routing Problem with Time Windows.

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"To be uncertain is to be uncomfortable, but to be certain is to be ridiculous" - Chinese Proverb

Chapter 1

Introduction

As an introduction to the research conducted, the current situation of climate change regulation will be described first, in Sec 1.1. Second, the impact of the aviation sector on global warming is discussed in Sec. 1.1.1, followed by the climate agreements made with the aviation sector. Sec. 1.2.1 elaborates on ground-based activities, which is followed by the introduction of different taxi procedures in Sec. 1.2.2. Sec. 1.3 introduces the main problem that is studied in this thesis. This chapter ends with the research framework in Sec. 1.4, which includes the main research question, sub-questions, research goals, research scope, and a report outline.

1.1 Climate Change Regulations

Global warming is one of the biggest challenges of the current century. The large-scale emission of Green House Gasses (GHG) is the cause of global warming. The caused climate change results in e.g. rising sea level, severe weather events, decrease in freshwater availability, and a decline in bio-diversity [1–3]. The Paris Agreement of 2015 is set up to respond to global warming [4]. The goal is to keep the global temperature rise below 2 °C compared to pre-industrial levels and its ambition is to keep the temperature rise below 1.5 °C. All parties that signed, are responsible for about 97 % of global greenhouse emissions. All participating countries have made climate plans in which they describe how to achieve Carbon-dioxide (CO_2) emission reduction and how they will combat climate change.

The Dutch target is to reduce emissions by 49% in 2030 compared to 1990. The reduction of CO_2 in 2050 must be 95 % compared to 1990. These targets are stated in the Climate law (Klimaatwet) [5]. In order to achieve the emission reductions, the Dutch government, companies and Civil Society Organizations (CSO) signed the Climate Agreement (Klimaat Akkoord) [6]. This agreement includes plans and agreements between the parties in order to achieve the CO_2 reduction targets. Besides this, the Climate law also states that the Dutch government needs to set up a Climate Plan (Klimaatplan) [7]. This plan includes the main points of the policy with which the government is going to achieve the targets of the Climate law. This climate plan also includes the latest scientific insights into climate change and the economic effects of it.

All targets set by the UN and all individual governments, require an energy transition in many sectors. An energy transition is a transition from the current fossil fuel-based energy system to a low-carbon society based on renewable energy sources. Decision-makers need to make highly complex decisions in the process of creating a low-carbon society. These decisions need to maintain or even increase the current level of prosperity while considering multiple environmental, social, and financial objectives.

1.1.1 Aviation Sector Climate Agreements

The aviation sector includes all aspects of air travel. This also includes the activities supporting air travel. The aviation sector is a large and growing contributor to global warming. Before the COVID-19 pandemic hit, the aviation sector was expected to grow 5% annually, increasing its contribution to global warming [8]. Global aviation is responsible for 4.9% of global warming [9]. Besides the impact it has on global climate change, it also has a detrimental impact on human health due to aviation noise and air quality degradation near airports [10]. At airports, the landing and take-off (LTO) cycle are the major causes of emissions that contribute to the impact it has on human health [11, 12].

In order to reduce the impact on the climate and human health, the aviation sector is taking steps to reduce its emissions. The aviation sector has several reasons to become more sustainable. The first reason is the pressure from the government. By signing the Paris Agreement, the Dutch government commits itself to these targets, which directly affects the Dutch aviation sector. Also, the Dutch government states its ambition to be a front-runner in sustainable aviation innovation [13]. Being a front-runner of sustainable aviation innovation might offer national business opportunities. This ambition stimulates the aviation sector to focus on sustainability. A second reason why the aviation sector wants to reduce its emissions is social urgency. There is an increasing tendency of people to want flying to be less damaging for the environment [14]. A third reason why airports want an energy transition is that this might offer new business opportunities for the airports. Many new initiatives are being developed for sustainable flying from which an airport can profit, like domestic package delivery from the airport, usage of large drones for delivery, and the airport being used for domestic taxi flight services, i.e. Uber-like flight services [13, 15, 16].

Although international aviation is not included in the Paris Agreement, all 193 national governments, including the Netherlands, which are a member of the UN-organization International Civil Aviation Organization (ICAO) made agreements regarding aviation. They agreed in 2016 to halve their CO_2 emissions due to aviation activities by 2050 compared to 2005 [17]. Also, they agreed to a carbon-neutral growth starting in 2020.

In contrast to international aviation, domestic flights and ground operations at an airport fall under the legally binding Paris Agreement. The Dutch aviation targets are set in a time window till 2070. The feasibility of these targets and all plans to realize the required emission reduction are stated in the Draft Aviation Annotation (Ontwerp-Luchtvaartnota 2020-2050) [18]. The targets regarding aviation that must be met first, i.e. 2030 are, [19]:

- All ground-based aviation activities to be zero-emission.
- Electric taxiing to be the standard procedure.
- 15% reduction of emissions originating from domestic aviation compared to the emission level of 1990.
- The first 20-50 passenger electric aircraft to be operating.

An aviation activity that is zero-emission, does not emit any CO_2. So, an activity that emits CO_2, but the emission is compensated, is not a zero-emission activity. In addition, all electricity, hydrogen, or biomass used for zero-emission activities, need to be emission-free. For this research, we will focus on the zero-emission of ground-based activities and electric taxiing to be the standard procedure, as these require large investments, need to be realized in a relatively short time frame, and have a major impact on the daily operations at an airport.

1.2 Aviation Sustainability Targets

This section elaborates on the aviation sustainability targets that are studied in this research, the ground-based activities to be zero-emission in 2030 and electric taxiing becoming the standard procedure.

1.2.1 Ground-Based Activities

The first aviation sustainability target that is studied in this research, is the ground-based aviation activities to be zero-emission in 2030. Ground-based activities include, according to the Dutch Ministry of Infrastructure and Water Management [19]:

- Maintenance, energy supply, and handling of aircraft.
- Transportation of passengers, employees, luggage, and cargo at an airport, which are not on a taxiing aircraft.
- Energy and maintenance of all buildings of an airport.

Currently, ground-based activities account for about 1% of all CO_2 emissions of the aviation sector [15, 20]. The largest contributors to CO_2 emissions originating from ground-based activities at an airport are the (Ground Power Units) GPUs and the pushback trucks. They are responsible for about 51% and 17% of the CO_2 emissions respectively [20].

GPUs provide aircraft electricity during the turn-around of an aircraft. This is the time between 2 consecutive flights of an aircraft. GPUs provide electricity for heating, onboard systems, and air conditioning. A GPU can be considered as a mobile diesel-fuelled generator. In order to reduce the emissions from GPUs, the usage of a GPU can be replaced by using a Fixed Power Unit (FPU). This is a socket in the wall of the main airport building which can provide an aircraft emission-free electricity, i.e. green electricity. Providing an aircraft with green electricity from a FPU instead of electricity from a GPU reduces half of all emissions originating from ground-based activities. The FPUs are already present at many airports. However, connecting an aircraft to a FPU requires heavy lifting and more personnel compared to using a GPU. In the next couple of years, it is expected that airports will start using the FPUs instead of GPUs to reduce emissions.

The second-largest contributor to emissions is pushback trucks. A pushback truck pushes an aircraft back from the gate. After a pushback truck performed the push, it is detached from the aircraft and the taxi procedure starts. Sec. 2.1 elaborates further on the current operations of pushback trucks.

1.2.2 Taxi Procedures

The second sustainability target that is studied in this research, is the electric taxi procedures. Taxi procedures of an aircraft are one of the largest contributors to emissions at an airport. Note, that these emissions are not regarded as emissions from ground-based activities.

After an aircraft lands, it taxis from the landing lane to the gate, or upon departure an aircraft taxis from the gate to the runway. This can be done in several ways. Currently, the most sustainable option is a form of taxiing in which all engines are off. Examples of sustainable taxiing are onboard systems that are powered by the Auxiliary Power Unit (APU) present on an aircraft. An APU is a kerosene fuelled generator that powers aircraft electricity. However, these systems are quite heavy (about 150 kg) and airlines want their aircraft to be as light as possible to reduce fuel consumption. The other option for sustainable taxiing is a ground-based system. Currently, the only ground-based sustainable taxiing vehicle is the Taxibot [21]. The usage of ground-based taxi systems depends on whether an airport has this equipment, while in the case of all other options of taxiing, the airline decides what form of taxiing is used. A Taxibot is a hybrid truck that can tow an aircraft from the gate to the runway at the same speed as taxiing on an aircraft's engines. Usage of a Taxibot is expected to save 4% - 9% of fuel per flight, depending on the duration of a flight, as an aircraft needs less fuel as the taxiing does not consume fuel [21]. Zero-emission taxiing is not possible as an aircraft's engine needs to warm up and cool down after landing. Also, the Taxibot does not take over the function of an APU. So, the (kerosene-fuelled) onboard APU still provides an aircraft with the electricity needed for onboard systems, starting of the engines and air-conditioning during a taxi trip performed by a Taxibot. Currently, there are no trucks on the market that also take over the function of the APU. However, companies are developing electric towing trucks that take over the function of an APU, to reduce the emissions at airports.

1.3 Energy Transition

In order to meet the sustainability targets mentioned in Sec. 1.1.1, airports need to make many decisions. How will they achieve zero-emission ground-based activities and how will electric taxiing be the standard? What investments need to be made? How will the operations change? Many actors play a role and each actor has its own interests. Airports are responsible to meet the sustainability targets, while the Ground Service Handlers (GSH) are responsible for the Ground Service Equipment (GSE) and the handling of the GSE. Also, when an airport decides to choose to go for a type of taxiing that takes longer than the current way of taxiing, airlines might be disadvantaged, as the turn around may take longer and they can perform fewer flights per day.

When focusing on what GSE to invest in, first needs to be decided what fuel-based GSE to invest in. The most common types are hydrogen, electricity, and biomass [22]. The most important factors, in deciding to invest in what, for each type of fuel-based GSE, are:

- Total cost of the new equipment
- Cost of man-hours needed to operate the equipment
- Fuel/electricity costs
- Speed at which the new equipment operates
- Costs of new infrastructure needed to operate the equipment

In order to have an idea of the impact of these factors, the daily operations of each potential type of new equipment must be studied in order to be able to compare them. In this research, we focus on the daily operations of one type of these options. We focus on fully electric towing trucks that provide an aircraft with all electricity, such that an aircraft does not need to use its APU. We choose to study electric trucks, as they require the largest operational changes compared to hydrogen or biomass fuelled trucks, as the electric trucks need to be charged at a fixed charging station, while the other trucks may be filled anywhere at the airport. However, there is already infrastructure for electric GSE present at airports, such that (large) investments may not be necessary for the implementation of electric towing trucks, compared to trucks that are fuelled by another source. A large disadvantage of electric towing trucks, and thus a possible reason why airports do not choose electric towing trucks, is that the change in operations is large. By studying the operational changes for the electric case, more will be known about the feasibility and costs of electric trucks. Also, as the battery technology rapidly increases [23–25], optimal charging strategies will become more important. Besides this, many companies are developing electric aircraft, which would lead to an increase of batteries that need to be charged at an airport [26]. Determining optimal charging strategies can be potential of great use for other electric vehicles at an airport, for example when electric aircraft are introduced.

In addition, we will focus on the impact of uncertainty of the arrival and departure times of aircraft at an airport on the operations of electric towing trucks. Delay of aircraft is very common and due to this delay, trucks must pick up aircraft at another time. The delay of these aircraft may be hours [27–29]. The effect of the delay must be considered when determining the operations of electric towing trucks, as it will have a large impact on the truck schedule.

1.4 Research Framework

1.4.1 Research Question

The research objective of this thesis is:

" to reduce the environmental impact of vehicles and stimulate the energy transition at airports to electric taxiing, increase the knowledge on electric vehicle routing problems (EVRPs) under uncertainty, by researching different models to describe such models under uncertainty "

This leads to the main research question:

" How can an adapted version of a vehicle routing problem describe the operations of electric towing trucks at an airport under uncertainty? "

1.4.2 Sub-questions

The sub-questions that will help answer the main research question are:

- How can one describe the operations of electric towing trucks at an airport by a deterministic Electric Vehicle Routing Problem?
- What techniques can include uncertainty of arrival and departure times of aircraft in an Electric Vehicle Routing Problem of electric towing trucks at an airport?
- What is the effect of the uncertainty on the solution of the EVRP?

1.4.3 Research Goals

The following goals are set in order to answer the research question:

- Develop a deterministic model to schedule electric towing operations at an airport given fixed arrival and departure times
- Develop a model that schedules electric towing trucks under uncertainty of arrival and departure times of aircraft at an airport

1.4.4 Research Scope

In order to be able to complete this research project within the limited amount of time, the objective of this research is scoped. The assumptions made demarcate the context of this research:

- This research focuses on all taxiing operations of commercial airlines, so cargo, general aviation, and military aviation are not included in this research.
- In this research, only fully electric trucks are considered, so no hybrid trucks.
- Additional investments needed in infrastructure are not considered, e.g. the construction of extra roads.
- Change in weather conditions that may affect the electricity consumption of electric trucks is not taken into account.
- Legality, e.g. with respect to working hour restriction, of the operations is not taken into account.
- Only uncertainty of arrival and departure times of the aircraft are taken into account since this has the largest impact on the planning of the trucks.
- Break-down of the trucks or truck driver mistakes / absence is not taken into account.

1.4.5 Report Structure

The structure of this thesis is as follows. First, a general introduction to a Electric Vehicle Routing Problem (EVRP) is given (Chap. 2). In this chapter, we discuss how the operations of electric towing trucks can be described in a general way. In addition, we discuss how to solve models that optimize the operations of electric towing trucks at an airport.

In Chap. 3, we present a deterministic EVRP. We discuss the decision variables (DVs) and we present the objective value and all constraints that together describe the model of a deterministic EVRP. In this chapter, we present the results obtained from this deterministic model and we discuss the results. In addition, we compare the deterministic EVRP with a deterministic Vehicle Routing Problem (VRP) of non-electric towing trucks, to indicate the impact of a change to an electric towing truck fleet at an airport.

As aircraft may be delayed, the arrival and departure times of aircraft at an airport may not be considered deterministic. This affects the operations of the electric towing trucks. In Chap. 4, we present a Robust Optimization (RO)-based model that describes the operations of the electric towing trucks under uncertain arrival and departure times of the aircraft. In Chap. 4 we motivate the specific RO-based method that is used. In this chapter, we present the results obtained from the RO-based model and we compare the results with the results obtained by the deterministic model presented in Chap. 3.

In Chap. 5 we present a second way to describe the operations of electric towing trucks at an airport under uncertain arrival and departure times. This model is a dynamic model that makes decisions throughout the day about what trucks must do next, considering the information about the actual arrival and departure times, that becomes available throughout the day. An algorithm to solve this Stochastic Sequential Decision Problem (SSDP) is presented. This Dynamic Approximated Cost Algorithm (DACA) determines at every decision epoch what the best action is, considering many sampled realizations of the arrival and departure times of aircraft. The results of this Stochastic Sequential Decision Model (SSDM) are presented and discussed in this chapter. These results are compared with the results obtained from the deterministic model and the RO-based model.

In Chap. 6 we state our conclusions. We finalize this thesis with Chap. 7, where we discuss this research project, according to 3 categories of discussion points. We discuss (1) general points of discussion that apply to all models presented in this thesis, (2) discussion points regarding the models that take into account the uncertainty of arrival and departure times, and (3) we present additional ideas for EVRPs.

Chapter 2

Scheduling of Electric Towing Trucks

One of our research goals is to develop a schedule of electric towing trucks at an airport. The goal of this chapter is to introduce how an Electric Vehicle Routing Problem (EVRP) can be formulated and solved. Before we describe how an EVRP can be formulated, we must understand the current and future daily operations at an airport. This is described in Sec. 2.1. This is followed by a brief description of the electricity usage of the electric towing trucks. In Sec. 2.2, an introduction to a Vehicle Routing Problem (VRP) is given and described how one can formulate an EVRP. And in Sec. 2.3 is explained how the EVRPs in this thesis are solved. In Chap. 3, we continue by presenting the mathematical formulation of the EVRP of electric towing trucks at an airport.

2.1 Change of Operations due to Electric Towing Trucks

Operations differ from airport to airport and sometimes even from airline to airline at an airport. One description of all daily operations or one description of the future operations at an airport can not be given. However, after talking to ground service handler companies, we state a generally accepted description of the current and future operations at an airport. Currently, almost all aircraft will taxi on (a number of) their engines from the landing lane (gate) to the gate (runway). For this thesis, we consider that all aircraft will be towed by an electric truck from the runway to the gate (or vice versa). The truck is attached to the aircraft. Currently, most aircraft are attached to a diesel-fuelled Ground Power Unit (GPU) during turn-around and in the future all, aircraft will be connected to an electricity-powered Fixed Power Unit (FPU). The last main difference in operations is regarding the power supply during the taxi procedure. Currently, most aircraft are powered by the on-board Auxiliary Power Unit (APU) during the taxi procedure. For this research project, we consider that the electric towing truck provides an aircraft with electricity during a taxi trip.

2.1.1 Electricity Consumption During a Tow

When determining the operations of electric towing trucks, we must take the electricity usage of the towing trucks into account, as a truck needs to charge when its battery is empty. In Appendix A, the details of this estimation are presented. Here we explain which factors are taken into account. While moving, trucks may either be towing an aircraft or driving around the airport while not towing an aircraft. For this thesis, it is assumed that a truck uses constant power overtime for driving empty or towing an aircraft. This way, the electricity usage depends on the duration of the drive or tow. Here we categorize the electricity usage in two parts: (1) a truck needs electricity to drive or tow and (2) it needs electricity to provide an aircraft with electricity during the tow.

While a truck moves, we consider that the electricity needed depends on the weight of an aircraft in the case of towing and the speed at which the truck drives. When the weight of the aircraft, the towing speed, and the time needed to tow, are known, one can determine the electricity needed for the tow. Here we also take into account that a departing aircraft weighs more than an arriving aircraft, as arriving aircraft have used most of the kerosene. All details on the exact power required while driving/towing are given in Appendix A.

In addition to the electricity needed for the actual towing/driving, electricity is needed to provide an aircraft with electricity during the tow. There are 3 main processes that need electricity from the towing truck. First, electricity is needed for on-board systems, such as lighting. The amount of electricity needed for on-board systems depends on the size of an aircraft. The second main consumer of electricity is air-conditioning. The amount of electricity needed for air-conditioning depends on the size of the aircraft and the outside temperature. Lastly, departing aircraft need electricity to start the engines. The power needed to start the engine depends on the size of the aircraft. The amount of electricity needed for on-board systems and air-conditioning, is proportional to the towing time, while the electricity needed for the engine starter is fixed. All details regarding the exact amount of electricity needed to provide aircraft electricity during the tow, are given in Appendix A.

2.2 (Electric) Vehicle Routing Problems as a Mixed Integer Linear Program

There are many situations in which one wants to know for a fleet of vehicles what the (sub-)optimal operations are. A package delivery service may want to know what routes their trucks need to drive in order to deliver all packages. A taxicab company may want to determine which driver goes to which customer. Formulating a mathematical model that determines for a fleet of vehicles which goes where at what moment in time, can be done in many ways. That is the wonderful thing about mathematics: one can decompose a real-life situation till it is an abstract representation of reality, but you can also lose yourself in complex theories, trying to obtain a more realistic representation of the problem. By determining how to model a routing problem of electric towing trucks, this is no different. There are many ways to represent this problem and many ways to solve it. The question is always: what is the most suitable method to describe the real-life situation? The basis for all mathematical decision models that determine the routes for a fleet of vehicles, is a Vehicle Routing Problem (VRP). For the EVRP, we focus on an adapted version of a VRP. Here we will elaborate on the adapted version of a VRP to describe the operations of electric towing trucks at an airport.

The first description of a VRP is of G. Dantzig *et al.* in 1959, where they describe a truck dispatching problem [30]. In this problem, the optimal routing of a fleet of gasoline trucks is determined between a terminal and service stations that are supplied by the terminal. This model generalizes the famous Travelling Sales Problem. VRPs are widely used in industry [31–37] and many variations to the VRP stated by Dantzig *et al.*, are introduced [38–43]. A VRP is a combinatorial optimization and integer programming problem. It usually determines how goods are delivered from a depot to customers by a fleet of trucks. An optimal solution of a VRP is a set of Decision Variables (DVs) that describe (timed) routes such that all requirements are met and the costs are minimized. These requirements may be customer (specific) requirements or operational constraints. The costs that are minimized, may be e.g. the total travel time, total distance traveled, fuel costs, operational costs, or total tardiness.

The routing problem of electric towing trucks at an airport can be considered as trucks that need to pick-up goods (an aircraft) at a location to drop it off at another location. Electric towing trucks will pick up aircraft at the exit ramp (gate) and deliver them at the gate (runway). This differs from the classical VRP, where trucks leave from a depot and deliver goods at various locations consecutively. Another difference compared to the classical VRP is that electric towing trucks have a limited battery, such that they must return to a (fixed) charging station before they run out of battery. Lastly, aircraft arrive and depart at specific times, such that the aircraft needs to be served in a specific time-window. All these characteristics of the situation may be described by combining several VRPs.

A VRP where goods need to be picked up and delivered, like in the case of electric towing trucks at an airport, is known as a Vehicle Routing Problem with Pick-up and Delivery (VRPPD). Examples of such models are presented in [39, 42–44]. In the case of electric towing trucks, the aircraft needs to be delivered at a certain location directly upon pick-up. No other goods (aircraft) may be picked-up before a truck delivers its good at the drop-off location. This can be realized by adding the so-called Last In, First Out (LIFO) constraint. This constraint is used in many models, among which [39, 42, 45, 46].

The aircraft needs to be picked up in a small and specific time-window. A VRP where goods need to be delivered in a specific time-window is known as Vehicle Routing Problem with Time Windows (VRPTW). This widely used version of a VRP, can be used for problems where, for example, goods are needed at a specific time, or in cases where the locations that the goods need to be dropped off, have specific opening hours. In a VRPTW, a time constraint is added for each delivery.

Lastly, the electric towing trucks may not run out of battery and need time to recharge at a (fixed) charging station.

VRPs are usually modeled as a Mixed Integer Linear Program (MILP). Here some decision variables (DVs) have integer constraints, while other DVs are continuous variables. In a VRP, usually, the DV that determines whether a truck drives to a specific location or not is a binary DV. In contrast, the DV that determines at what moment in time a truck drives, is usually a continuous DV.

Definition 2.2.1 (Mixed Integer Linear program)**.** A Mixed Integer Linear Program (MILP) is a problem with a linear objective function $f^T x$, where f is a column vector of constants and x is a column vector of unknown decision variables. A MILP has bounds, linear constraints, no non-linear constraints, and some DVs are constrained to be an integer. The set of indices of the integer constrained DVs is denoted I.

$$\begin{aligned} \min \quad & f^T x \\ \text{s.t.} \quad & Ax \le b \\ & x_i \in \mathbb{Z}, \quad \forall i \in I \end{aligned} \tag{2.1}$$

Definition 2.2.2 (Solution)**.** A solution to a MILP is defined as a setting of the decision variables.

Definition 2.2.3 (Feasible solution)**.** A feasible solution to a MILP is defined as a solution that satisfies all constraints of the MILP.

Definition 2.2.4 (Optimal solution)**.** An optimal solution to a MILP is defined as a feasible solution with the minimal (maximum) objective function value of the MILP in case it is a minimization (maximization) problem.

So in conclusion, to describe the operations of electric towing trucks at an airport, we formulate a special EVRP. This EVRP will be an adapted version of a VRPTW and a VRPPD with LIFO constraints. Additional constraints concerning the battery level of trucks are introduced to describe an EVRP instead of a VRP. The mathematical description of the vehicle routing problem of electric towing trucks at an airport is given in Chap. 3. This EVRP is described as a MILP.

2.3 Solving a Mixed Integer Linear Program by a Branch-and-Bound Algorithm

The basis of the solving techniques used to solve MILPs, is the *branch-and-bound algorithm*, schematically depicted in Fig. 2.1.

The branch-and-bound algorithm first converts a MILP to a *relaxed version*. This relaxed version is the MILP without all integer restrictions. So all DVs may be continuous. The relaxed MILP is a Linear Program (LP). We denote the original MILP as P_0. P_0 is depicted in Fig. 2.1, as the white dot at the top of the figure. The LP is then solved, hoping the solution satisfies the integer restrictions. However, as the integer constraints are not specifically stated, most likely the solution does not satisfy the integer constraints. If indeed, the solution does not satisfy the integer restrictions, there are DVs whose value is fractional. For example, the DV $x = 22.3$, then 2 restrictions can be added: $x <= 22$ and $x >= 23$. Two new MILPs are created, P_1 and P_2 one for each restriction. This is depicted in Fig. 2.1 as the two white dots below the top white dot. The DV of these restrictions, x, is called the *branching variable*. The best solution of the 2 sub-MILPs, P_1 and P_2, is optimal to the original problem, P_0. The same idea can be applied to the sub-MILPs. The LP relaxations of these MILPs are computed and if necessary new branching variables are selected. When repeating this procedure, one creates a search tree. The sub-MILPs are called the *nodes* of the tree and P_0 is the *root node*. The leaves of this tree are all nodes that have not yet been branched. If one can solve or dispose of all leaf nodes, the original MILP, P_0 is solved. A node is denoted as *fathomed* if a node is no longer branched. These nodes are depicted as the green dots in Fig. 2.1. This can happen in the case (1) that by branching and thus adding a restriction, the LP becomes infeasible. The second case, in which a node is denoted as fathomed, (2) concerns finding a solution of the LP that satisfies all integer restrictions.

If during the process of bounding and branching, a solution of a LP-relaxation satisfies all integer restrictions, we know that this a (feasible and possible optimal) solution of our original MILP, P_0. This node is then denoted as fathomed and this node is no longer branched. In addition, the best solution that satisfies the integer restrictions is denoted as the *incumbent*. This is depicted as the purple dots in Fig. 2.1. If the currently found solution is better than the current incumbent or in the case that this is the first found solution, the incumbent is updated.

In the case of a minimization problem, like the EVRP as will be shown in Chap. 3, the *optimality gap* of a MILP is determined by the difference in the so-called current *upper bound* and *best bound* (or sometimes called the lower bound). The upper bound is the objective value of the incumbent. The best bound is in case of a minimization problem, the minimum of the optimal objective values of all current leaf nodes.

The optimality gap of LPs is usually a good measure of the solution. However, the optimality gap of a MILP is not necessary a good measure of the solution. The best bound is the optimal objective value of all current leaves. Some of these leaves, do not contain all integer constraints of the model. When a problem contains many integer DVs, this best bound may be way better, such that the gap is very large. This is also the case for most MILPs solved for this project. As a result of many integer DVs, the best bound is always 0, as there are leaves where not all integer restrictions are taken into account. The upper bound is either 0 or a non-zero value if the MILP is feasible. In the case that the upper bound is 0, the optimality gap is 0 and this is the optimal solution. In the case of a non-negative upper bound, the optimality gap is 100% as the best bound is 0. This is why a maximum solving time must be set to stop solving, as the model will continue to solve till it finds a solution with an objective value equal to zero. We introduce the term: *a best-found solution*.

Definition 2.3.1 (Best-found solution)**.** The best-found solution of a MILP is defined as the feasible solution with the lowest objective function value, that is found within the maximum solving time.

There are many techniques to improve the solving process of the branch-and-bound algorithm. State-of-the-art solvers use many techniques to improve the performance of the branch-and-bound algorithm to solve MILPs. Among the most important techniques are *pre-solve*, *cutting planes*, *heuristics*, and *parallelism*. Pre-solve is done in order to deduce the size of the problem and to formulate a problem more tightly. Cutting planes, which is a whole field of research of its own, is in short, a way of tightening the formulation of the problem during solving, without creating more sub-problems. Heuristics are of great importance for finding good solutions very early in the process of solving. As a maximum solving time is set to solve the EVRPs of this project, we would like to have good solutions as fast as possible, such that we are most likely to have good solutions when the maximum solving time is reached. Heuristics are implemented in the commercial solver that we use, Gurobi, to do a little extra work to explore whether a node might have a good integer feasible solution. Lastly, most solvers run in parallel, as nodes may be processed independently.

Before presenting the mathematical model, some specifics about the implementation of the mathematical model must be noted. All mathematical models presented in this thesis are coded in Python 3.7. The mathematical models are implemented using the Pyomo 5.7.1 package [47] and are solved by the state-of-the-art commercial solver Gurobi 9.0.3 [48]. The Python-based Pyomo package is a widely used package for describing optimization problems. Pyomo was chosen as an optimization problem described as a MILP can be implemented intuitively and the package is compatible with many (commercial) solvers. The Gurobi solver is used as it contains state-of-the-art solving techniques and does not require a connection with a cloud, compared to other commercial state-of-the-art solvers.

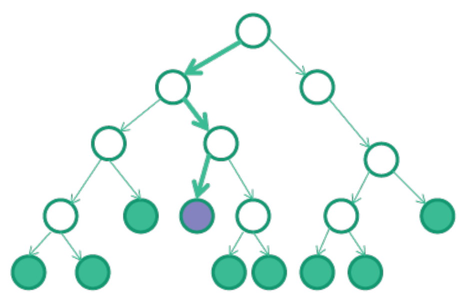


Figure 2.1: Schematic overview of the branch-and-bound algorithm, adapted from [49].

Chapter 3

Deterministic EVRP

To first consider the daily operations of electric towing trucks at an airport, without taking the uncertainty of arrival and departure times into consideration, a deterministic model that determines the daily operations of electric towing trucks at an airport is presented. This mathematical model is introduced in this chapter. In Chap. 4 and Chap. 5, the impact of the uncertainty in arrival- and departure times are studied. From the best-found solution of the deterministic Electric Vehicle Routing Problem (EVRP) introduced in this chapter, a schedule for all trucks can be derived. This includes when the towing trucks will travel and when they will return to the charging station to charge and for how long they will charge.

In Sec. 3.1.1-Sec 3.1.3 all parameters, sets, and decision variables of the deterministic EVRP are introduced. This is followed by the objective function and all constraints. Comments on the implementation of this EVRP are given, followed by an analysis of the best-found solutions of this EVRP in Sec. 3.4. Some extensions to this EVRP are done to make the model more realistic. The extensions and the analysis on the best-found solutions of the EVRP with extensions are presented in Sec. 3.5. This chapter is finalized with a comparison between the usage of electric and non-electric trucks at an airport in Sec. 3.7.

3.1 Description of a Deterministic EVRP

In this section, the elements of the deterministic EVRP of electric towing trucks at an airport are discussed. For this deterministic EVRP, the flight schedule including all arrival- and departure times, start and end location of the tow are considered deterministic.

3.1.1 Sets and Indices

Here we discuss the sets and indices used throughout this chapter.

Sets

I: Set of requests, a request is considered as the job to tow an aircraft from a start location to a destination location.

D: Set of depots, where the charging stations are present. In this deterministic EVRP, a single depot is considered: $D = \{d\}$.

K: Set of trucks, a homogeneous fleet is considered.

Indices

$i, j \in I \cup D$: i, j are elements of the set of requests, I, or elements of the set of depots, D.

$k \in K$: k is an element of the set of trucks, K, so k represents a specific truck.

It might not seem obvious at first, why we define i, j to be an element of the set of requests, I or of the set of depots, D. However, these indices will be used to distinguish Decision Variables (DVs) and for some constraints it is necessary to make a distinction between cases where i, j are an element of I or of D. For example, in the set of constraints of Eq. 3.4.

3.1.2 Decision Variables

There is a lot of literature available on all kinds of variations of VRPs. In this literature, many different kinds of DVs are discussed. In most studies on VRPs, a binary DV, e.g. $x_{i,j,k}$, is introduced to indicate a truck drives from one place to another [43, 44, 50]. Here i, j are the places and k the truck. One can choose to let i and j be a point in the graph or to let i and j be the actual locations of a customer or one can choose to indicate a specific customer by i and j. For VRPs where the vehicles leave and come back to a depot several times during the day (or any other time-window), like for electric towing trucks, different ways of formulating the DVs are covered in literature. In some studies, the concept of a *trip* is introduced. A trip consists of all nodes/locations visited consecutively by a truck between leaving the depot and arriving at the depot again. The binary DVs of such studies include a trip number, $x_{i,j,k,r}$, where r is the trip number [25, 32, 51]. We choose not to use the concept of trips, as this would significantly increase the DV set.

For this thesis, we use the binary DV, $x_{i,j,k}$, where i and j are requests or depots and k a truck. This is chosen as some constraints of our deterministic EVRP can be formulated intuitively. For example, we want to include the constraint that all aircraft are towed exactly once. This constraint is described by Eq. 3.3 and is discussed in Sec. 3.1.5. This constraint can be formulated as exactly one $x_{i,j,k}$ must equal 1 for every i in the set of requests. If we choose to use a set of binary DVs, $x_{i,j,k}$, for which i and j are locations, it would be difficult to formulate a constraint that all aircraft must be towed. In addition, if we choose i and j to be nodes in a graph of the airport, the EVRP must also determine the shortest route to drive, while solving. In this EVRP, we determine the shortest route between requests i and j and use this distance, the time needed and the electricity needed as input parameters for the EVRP. This way, the shortest route does not have to be determined while solving the EVRP.

An overview of all DVs:

<u>$x_{i,j,k}$, $i, j \in I \cup D$, $k \in K$: binary DV.</u>
This DV describes which requests are handled consecutively by truck k. If $x_{i,j,k} = 1$, truck k will go to request j after i. Here, i, j can be an element of I or D. For example, if $x_{i,j,k} = 1$ and $i \in D$ and $j \in I$, truck k will leave a depot to go to the start location of request j. While, if $i, j \in I$, truck k will first tow the aircraft of request i from its start location to its destination and then drive to the start location of request j. Lastly, if $i \in I$ and $j \in D$, truck k will tow the aircraft of request i to its destination and then return to the depot. In order to reduce the number of DVs, the DVs $x_{i,j,k}$ for which hold that the start time of the tow of request i is later than the start time of the tow of request j, are not included. This can be done, as request i will not be towed before j, as its start time must be later than that of request j.

<u>s_i, $i \in I$: continuous real non-negative DV.</u>
This DV decides the start time of the tow of request i.

t_i, $i \in I$: continuous real non-negative DV.
This DV decides how long a truck will charge after it served request i. This DV can only be non-zero when $x_{i,j,k} = 1$, where $i \in I$ and $j \in D$.

q_i, $i \in I$: continuous real non-negative DV.
This DV indicates the battery level of a truck at the start of towing the aircraft of request i. One could argue that this DV is redundant, as the battery charge of a truck can be constructed by adding all charged electricity and subtract all electricity used up till the start of request i. However, this requires multiplication of DVs $x_{i,j,k}$ and t_i, which most MILP solvers do not accept, although $x_{i,j,k}$ is a binary DV. In addition, the number of constraints does not decrease when q_i is not introduced. Also, the readability of the mathematical model decreases, as the load would have to be represented by:

$$q_i = \sum_{\substack{i' \in I:\ s_{i'} \leq s_i \\ k \in K}} x_{i',d,k} \cdot t_{i'} \cdot \mathcal{C}_s - \sum_{\substack{i', j' \in I:\ s_{j'} \leq s_i \\ k \in K}} x_{i',j',k} \cdot q_{i',j',k}. \tag{3.1}$$

Here, the first part of the right-hand side (RHS) represents the amount of electricity charged up till the start of request i. $\mathcal{C}_s$ represents the charging speed. The second part of the RHS represents the electricity used up till the start of request i. $q_{i,j,k}$ is the electricity used when $x_{i,j,k} = 1$, the next section elaborates on the value of $q_{i,j,k}$.

3.1.3 Parameters and Input Data

$\mathcal{C}_s$: Charging speed in kW/h

$\mathcal{C}_c$: Maximum capacity of the trucks

In order to determine the electricity used to tow a certain aircraft, a flight schedule must be known. Also, the distances that a truck needs to travel and the corresponding towing and driving times must be known. Here, we elaborate on the electricity used and travel times.

Flight schedule

For this thesis, data of the busiest days of the year at Rotterdam-Airport is used. On these days ± 50 flights arrive or depart at the airport. For this deterministic EVRP, this data is considered known. This data includes:

$t_i^{a,d}$ $i \in I$: Arrival/departure time of the arriving aircraft of request i

$l_i^{a,d,s}$ $i \in I$: Start location of arriving/departing aircraft of request i

$l_i^{a,d,e}$ $i \in I$: Destination location of arriving/departing aircraft of request i

For all $i \in I$, a time-window in which a truck needs to start to tow the aircraft of request i is determined by $t_i^{a,d}$:

$[e_i, l_i]$: Time-window in which a truck needs to start to tow the aircraft of request i. It is assumed that this is just a couple of minutes before and after $t_i^{a,d}$.

Distances, travel times and electricity usage

In order to know the distances traveled, a graph is created from the aerodrome chart of the Rotterdam-Airport, which is included in Appendix B. A scale is included in this aerodrome chart, such that the shortest distances between gates, runways, and exit gates can be calculated from the aerodrome. This is done by using Dijkstra's algorithm.

The time duration of each DV $x_{i,j,k}$, can be calculated from these distances. It is assumed that the speed of a truck is 14 km/h when towing an aircraft and is 30 km/h when a truck is driving while not towing an aircraft. It is assumed that these speeds are constant while a truck drives. Note, DVs $x_{i,j,k}$ where $i \in D$ and $j \in I$, describe that truck k goes from the depot to the start location of request j. So, $t_{i,j,k}$ where $i \in D$ and $j \in I$, includes the travel time of a truck driving empty, i.e. not towing an aircraft, from the depot to the start location of request j. Likewise, for $x_{i,j,k}$ where $i, j \in I$, describe that truck k tows the aircraft of request i from its start location to its destination and then drives empty to the start location of request j. So, $t_{i,j,k}$ where $i, j \in D$, include the travel time of the tow of request i and the time that truck k drives empty from the destination location of request i to the start location of request j.

$t_{i,j,k}$, $\quad i, j \in I \cup D, k \in K$: $\qquad$ Time duration of $x_{i,j,k}$

The amount of electricity associated with the DV $x_{i,j,k} = 1$, is determined by the sum of electricity needed for the towing, driving empty and electricity needed for all other systems, e.g. air-conditioning and on-board systems, as explained in Appendix A.

$q_{i,j,k}$, $\quad i, j \in I \cup D, k \in K$: $\quad$ Electricity associated with the DV $x_{i,j,k}$

3.1.4 Objective Function

In a Vehicle Routing Problem (VRP), one can choose different objectives. For example, one can choose to minimize the travel time or the number of trucks or one could also be interested in maximizing the number of customers visited. In this thesis, we choose to minimize the electricity costs. This is chosen, as the number of trucks is usually fixed at an airport and given this amount of trucks, one can determine what the optimal truck schedule is, such that the electricity costs are minimal. We consider the electricity costs per kWh to be constant over time, so the objective is to minimize the total time charged,

$$\text{Minimize} \quad \sum_{i \in I} t_i \tag{3.2}$$

This deterministic EVRP minimizes the total charge time. The time charged at the depot after serving request i is defined by the DV t_i, which is only positive if $x_{i,j,k} = 1$ where $i \in I$ and $j \in D$.

3.1.5 Truck Moving Constraints

In this subsection, we discuss all constraints regarding the movements of trucks and the order in which the trucks may or may not drive. First of all, we want all aircraft to be towed exactly once. This is ensured by the set of constraints,

$$\sum_{\substack{j \in I \cup D \\ k \in K}} x_{i,j,k} = 1, \quad \forall i \in I. \tag{3.3}$$

This set of constraints states that summing over all DVs that have request i as its first index, must equal exactly one, for every i in the set of requests. Resulting in all requests being served once.

Constraints must be stated such that the order in which a truck serves different requests is clear. For example, a truck may leave the depot to go to a start location of a certain request, i, but then it must serve it and go to another request or return to the depot. This is an adapted form of a VRPPD with LIFO-constraint. Here we add that a truck cannot go to another aircraft, while it is towing one. This chaining of the operations of a single truck is done by the following constraints,

$$\sum_{i\in I\cup D} x_{i,j,k} - \sum_{i\in I\cup D} x_{j,i,k} = 0, \quad \forall j \in I,\ \forall k \in K. \tag{3.4}$$

This set of constraints states that if a truck k arrives at the start location of request j, this is when $\sum_{i\in I\cup D} x_{i,j,k} = 1$, it must go to another request afterwards or return to the depot. This is the case when $\sum_{i\in I\cup D} x_{j,i,k} = 1$. Otherwise, these sums must equal 0. This must be valid for each request $j \in I$ and each truck $k \in K$. This way, all operations are chained correctly.

The third set of constraints regarding the movements of a truck, states that trucks that leave the depot must return to the depot. As trucks must not be scattered around the airport at the end of the day, constraints are formulated to ensure that trucks return to the depot,

$$\sum_{i\in I} x_{d,i,k} - \sum_{i\in I} x_{i,d,k} = 0, \quad \forall k \in K. \tag{3.5}$$

These constraints make sure that when a truck k leaves a depot n times during the day ($\sum_{i\in I} x_{d,i,k} = n$), it must return to the depot exactly n times ($\sum_{i\in I} x_{i,d,k} = n$).

The last set of constraints that are specifically concerning the movements of the truck, is about trucks being only allowed to leave the depot, when they are actually present at the depot. If this set of constraints is not added, trucks will be assigned to go to aircraft, while they are not present at the depot. This set is formulated as,

$$x_{d,j,k} \le 1 - \left| \sum_{i\in I:\ s_i<s_j} x_{d,i,k} - \sum_{i\in I:\ s_i<s_j} x_{i,d,k} \right|, \quad \forall j \in I,\ \forall k \in K. \tag{3.6}$$

When the number of times that a truck left the depot ($\sum_{i\in I:\ s_i<s_j} x_{d,i,k}$) and returned again at the moment in time the truck wants to leave ($\sum_{i\in I:\ s_i<s_j} x_{i,d,k}$), are equal, a truck must be present at the depot and it may leave to go tow an aircraft.

3.1.6 Time Constraints

In this subsection, the sets of constraints regarding the time a truck starts to tow an aircraft of a request are discussed. First, the start of a tow of request i must be within its time-window. Here we add the time-window constraint of a Vehicle Routing Problem with Time Windows (VRPTW). This is formulated for our EVRP as,

$$e_i \le s_i \le l_i, \quad \forall i \in I. \tag{3.7}$$

The constraints of Eq. 3.7, constrain the starting time of each request to be within the time-window of that request. For this research project, we set $e_i = 0$ and $l_i = t_i^{a,d} + 5$, $\forall i \in I$. Here $t_i^{a,d}$ is the arrival or departure time of request i. So we constrain the tow to start no later than 5 minutes after the aircraft arrived.

In the second set of constraints regarding time, we constrain that requests i and j may only be handled consecutively if the truck can be on time at the start location of request j,

$$s_j \ge \max\{s_i, t_i^{a,d}\} + t_{i,j,k}, \quad \text{if } x_{i,j,k} = 1,\ \forall i, j \in I,\ i \ne j,\ \forall k \in K. \tag{3.8}$$

These constraints state that if a truck k goes to request j after serving request i (so $x_{i,j,k} = 1$), the time truck k start to tow j must be at least the start time of the tow of request i plus the time it takes to tow the aircraft of request i to its destination and then drive empty to the start location of request j (this is $t_{i,j,k}$). This must be the case for all different combinations of requests, for every truck. In addition, if the truck arrives at the starting location of request j, before the aircraft has landed, it must wait till the aircraft is there.

The last set of constraints regarding the start time of the requests, is about the start time of requests that are served by trucks that just left the depot. These requests can only be towed by a truck if there is enough time between the previous tow, the time spend at the depot and the start of the tow now. This is formulated as,

$$s_j \geq s_i + t_{i,d,k} + t_{d,j,k} + t_i, \quad \text{if } x_{i,d,k} = 1 \wedge x_{d,j,k} = 1, \ \forall i, j \in I, \ t_j^{a,d} > t_i^{a,d}, \ \forall k \in K. \tag{3.9}$$

If truck k goes to the depot after serving request i, $x_{i,d,k} = 1$, and if a truck k serves request j after it departs from the depot, $x_{d,j,k} = 1$. If this is the case, the start time of the tow of request j must be at least the start tow time of request i (this is s_i) plus the time to serve request i and to drive to the depot (this is $t_{i,d,k}$), plus the time it takes to drive from the depot to the start location of request j, (this is $t_{d,j,k}$) plus the charging time, t_i. This constraint must be valid if $x_{i,d,k} = 1$ and $x_{d,j,k} = 1$, for all combinations of $i, j \in I$. For computational reasons, we state that this must only be valid for $i, j \in I$ for which holds $t_j^{a,d} > t_i^{a,d}$ and for all trucks $k \in K$. This reduces the number of constraints, as we know that if $t_j^{a,d} > t_i^{a,d}$, request i cannot be served before j. So constraints regarding these combinations are not included.

3.1.7 Battery Level Constraints

In this subsection, we discuss all constraints regarding the battery level of the trucks. One assumption must be noted. We assume that all trucks are fully charged at the beginning of the day and may be fully empty at the end of the day. This assumption is valid as the last flights of the day at Rotterdam Airport are around 11 p.m., while the first flights in the morning are around 7 a.m. There is enough time in between these flights, for a truck to fully charge.

The first set of constraints regarding the electricity level of trucks are about the maximum and minimum the battery level of a truck may be,

$$q_{i,d,k} \leq q_i \leq \mathcal{C}_c - q_{d,i,k}, \quad \forall i \in I, \ \forall k \in K. \tag{3.10}$$

The constraints of Eq. 3.10 ensure that the battery level of a truck k at the start of a request i, is always between the maximum capacity of the battery, $\mathcal{C}_c$, minus the electricity used to drive to the start location of request i, and the electricity needed to tow the aircraft of request i to its destination and then drive empty to the charging station. These constraints are needed to limit the electricity level to its maximum capacity and to ensure that a truck is always able to perform the tow and return to the charging station again.

The second set of constraints that we state about the battery level of trucks is about the battery level at the start of a tow,

$$q_j \leq q_i - q_{i,j,k}, \quad \text{if } x_{i,j,k} = 1, \ \forall i, j \in I, \ i \neq j, \ \forall k \in K. \tag{3.11}$$

These constraints state that if truck k serves request i and then goes to the start of request j (this is if $x_{i,j,k} = 1$), the battery charge of the truck at the start of request j, must be at most the battery charge at the start of request i minus the electricity consumed by serving request i and driving from the destination location of request i to the start location of request j (this is $q_{i,j,k}$).

The last constraints that we introduce are about the battery level of trucks that leave the depot. The battery level of a truck must be updated, if the truck charged at the depot,

$$q_j \leq q_i - q_{i,d,k} - q_{d,j,k} + \mathcal{C}_s \cdot t_i, \quad \text{if } x_{i,d,k} = 1 \wedge x_{d,j,k} = 1,\ \forall i, j \in I,\ t^a_j > t^a_i,\ \forall k \in K. \tag{3.12}$$

The constraints of Eq. 3.12 state that the battery level of truck k at the beginning of request j, after leaving the depot, must be at most the battery charge of truck k at the beginning of request i, minus the electricity used to tow request i, drive to the depot and drive to the start location of request j, plus the amount electricity charged at the charging station. This constraint must be valid if $x_{i,d,k} = 1$ and $x_{d,j,k} = 1$, for all combinations of $i, j \in I$ and for all trucks $k \in K$. Again, for computational reasons, only the constraints for which holds $t^a_j > t^a_i$, are implemented.

3.2 Mathematical Model Implementation

In this section, we will discuss some specific implementation methods used to implement the deterministic EVRP presented in previous sections, as a linear model. This is needed as most packages and solvers only accept linear operations.

The constraints of Eq. 3.6, contain absolute values, which is not a linear operation, such that it cannot directly be implemented in a MILP. This can be bypassed by rewriting Eq. 3.6 into the following form,

$$\begin{aligned} x_{d,j,k} &\leq 1 - \sum_{i \in I:\ s_i < s_j} x_{d,i,k} + \sum_{i \in I:\ s_i < s_j} x_{i,d,k}, \quad \forall j \in I,\ \forall k \in K, \\ x_{d,j,k} &\leq 1 + \sum_{i \in I:\ s_i < s_j} x_{d,i,k} - \sum_{i \in I:\ s_i < s_j} x_{i,d,k}, \quad \forall j \in I,\ \forall k \in K. \end{aligned} \tag{3.13}$$

All constraints that contain an *if*-statement, like the constraint of Eq. 3.8, 3.9, 3.11 and 3.12 need to be included to the MILP only if the *if*-statement is *True*. However, these *if*-statements include DVs, $x_{i,j,k}$, which are unknown when adding the constraints to the code. This can be bypassed by adding/subtracting $M(1 - x_{i,j,k})$ to a constraint, depending whether it is a $\leq$ or $\geq$ constraint. Here, M is a large number. For example, considering the constraint of Eq. 3.8. Only if, $x_{i,j,k} = 1$, the constraint needs to be valid. When subtracting $M(1 - x_{i,j,k})$ from the right-hand side of the constraint, the constraint is only of influence when $x_{i,j,k} = 1$. If $x_{i,j,k} = 0$, s_j may be smaller than the case if $x_{i,j,k} = 1$. So, the constraints of Eq. 3.8 are implemented as,

$$s_j \geq s_i + t_{i,j,k} - M(1 - x_{i,j,k}), \quad \forall i, j \in I,\ i \neq j,\ \forall k \in K. \tag{3.14}$$

The same is done for the other constraints that contain an *if*-statement, i.e. the constraints of Eq. 3.9, 3.11 and 3.12.

3.3 Process Overview

The complete model, including pre-processing (this includes among other things, determining the electricity and time needed for each x-DV), building the EVRP, solving it, and the post-processing, is implemented as a Python code using the Pycharm editor. The experiments are run on a laptop with Intel® Core™ i7-8650U CPU @ 1.90 GHz Processor with 16 GB RAM memory.

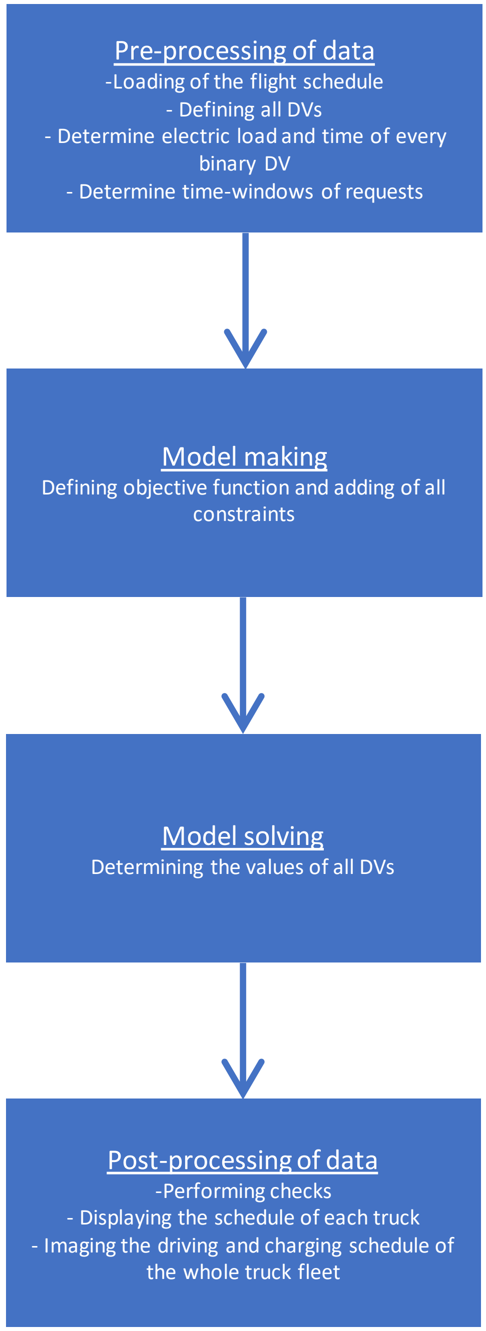


Figure 3.1: Flow chart of the pre-processing of the data, model making, solving, and post-processing of the data.

Once the EVRP is solved, the output consists of the DV values. The values of the DVs of the best-found solution are post-processed and visualized in a truck schedule. Also, several checks are performed to check whether all requirements are met. This is mainly done in order to check whether the constraints are implemented correctly and whether the post-processing of the solution is done properly. These checks include checking if all requests are served once and that they are served in time, checking whether towing, driving, and charging activities do not overlap in time for each truck. In addition to the visualized truck schedule, a detailed schedule of each truck is printed. This detailed schedule describes at what moment which truck must drive to which aircraft with what route. This detailed schedule also indicates the battery level of each truck during the day. An example of a detailed schedule is presented in Appendix B. A flowchart of the whole process is shown in Fig. 3.1.

3.4 Best-Found Solutions of the Deterministic EVRP

As explained in Sec. 2.3, a maximum solving time is set, such that we have a best-found solution, defined by Def. 2.3.1. This maximum solving time is determined per different problem that is solved, as a trade-off between the quality of the solution and the solving time. The best-found solutions of the EVRP, i.e. the found values of the DVs, are post-processed and depicted in a truck schedule. In this section, we present the truck schedules derived from the best-found solutions of the deterministic EVRP as described in Sec. 3.1. We will discuss the truck schedules while presenting them.

Fig. 3.2 shows the truck schedule obtained from the best-found solution of our EVRP. In this figure, the blue blocks correspond to the time that a truck is not present at the depot. A truck can either be driving empty or towing an aircraft or waiting at the end location of a certain request i to go to the start location of request j. The red blocks represent the time a truck spends at the depot charging. All white areas in this schedule, represent time waiting at the depot, not charging. Fig. 3.2 shows the truck schedule obtained from the best-found solution of our EVRP for a homogeneous fleet of 11 trucks for a flight schedule of the 25 first arriving and 25 first departing flights of "Day 1" of Rotterdam Airport. The minimum amount of trucks that are needed to serve all 50 aircraft of this day is 11. The EVRP is infeasible when only 10 trucks are available. The electricity capacity of the batteries is 150 kWh. The charging speed is such that the battery is charged in 4 hours (37.5 kW/h). We consider the charging costs to be € 1/min. The electricity costs for charging during the day are € 2428.97. If we add the charging costs in order to get the trucks fully charged at the beginning of the day, the total electricity costs are € 5068.97.

The first point to notice of this truck schedule is that all trucks charge exactly the amount of electricity that is needed to serve later requests and to be able to return to the depot. In the truck schedule, none of the trucks charge after they towed the last aircraft. The detailed schedule of each truck, confirms that indeed all batteries are completely empty at the end of the day. This is exactly what we would expect, in the case of a model that minimizes the total charging time.

Another point is that we see that this truck schedule is dependent on the flight schedule. If many aircraft need service at the same time, or in the same time interval, more trucks are needed to be able to serve all aircraft within the time-interval, as a result of a lot of electricity used by the trucks. That a truck schedule is dependent on a flight schedule, can be seen in Fig. 3.3. Here we see in Fig. 3.3a, the truck schedule for the same fleet, but for the flight schedule of one day later. However, all flights can be served by a fleet of fewer trucks. The minimum amount of trucks needed for this flight schedule is 9. The schedule of 9 trucks serving 50 flights of day 2, is shown in Fig. 3.3b. The electricity costs from the charging during the day of this flight schedule are higher, as more trucks need to charge, compared to the case of 11 trucks available. This is due to the assumption that all trucks are fully charged at the beginning of the day. However, the total electricity costs are higher for the truck schedule of 11 trucks. So from this, we can conclude that the truck schedule and thus the number of trucks needed, is dependent on the flight schedule.

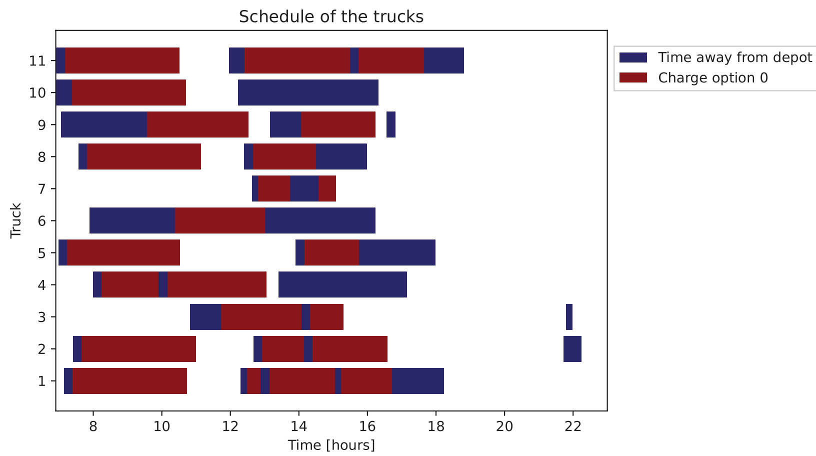


Figure 3.2: A truck schedule of a fleet of 11 homogeneous trucks for a flight schedule of 50 flights of day 1, where 5 minutes of service time is considered and all trucks have a capacity of 150 kWh. The total electricity costs are € 5068.97.

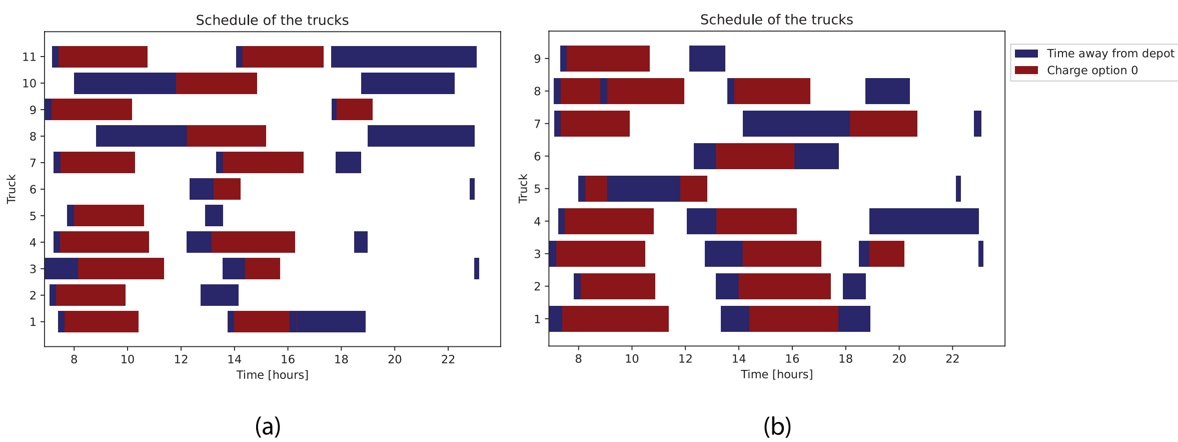


Figure 3.3: A truck schedule of a fleet of **(a)** 11 and **(b)** 9 homogeneous trucks for a flight schedule of 50 flights of day 2, where 5 minutes of service time is considered and all trucks have a capacity of 150 kWh, total charging costs are € 4756.16 (of which € 2116.16 due to charging during the day) in **(a)** and € 4421.72 (of which € 2261.72 due to charging during the day) in **(b)**.

3.5 Extensions to the Deterministic EVRP

The truck schedules shown in the previous section, show that the current deterministic EVRP is able to determine a truck schedule for a flight schedule while minimizing the charging time. However, there are opportunities to make this EVRP closer to the real-life situation. In this section, we present 3 extensions to the deterministic EVRP presented and discussed in the previous sections.

3.5.1 Different Charging Speeds

The first extension to the EVRP as presented in Sec. 3.1, concerns the charging speed. In reality, there may be more charging speeds at which a truck may be charged. There are a few advantages of being able to charge with different charging speeds. First of all, charging slowly is better for a battery and this will result in the battery lasting longer before it needs to be replaced [24, 52, 53]. As the trucks and batteries are expected to be relatively expensive compared to the electricity costs, it is important to take this into account. Introducing different charging speeds will also lead a truck schedule to be less dependent on a flight schedule. This will of course not bypass issues in the case of a number of aircraft need service around the same time. But allowing trucks to charge at different speeds will introduce more flexibility. Trucks have the option to go to the depot and charge fast when they are needed shortly after, while in the case that they are not needed for a long time, they can charge slow. So by introducing different charging speeds at which a truck may charge, may lead to a reduction of the total electricity costs and may result in batteries lasting longer before they need replacement.

By adding the opportunity for trucks to charge with different charging speeds, we introduce a set of charging speeds, $\mathcal{C}_s$. The subscript c, is added to the subscript indicating a visit to a depot, denoting with what speed the truck will charge: $x_{i,d_c,k}$. Consider that there are n different charging speeds. The set of elements of the set depots, D, is now larger, as an element is added for every charging speed: $D = \bigcup_{c=0}^{n} d_c$. In addition, the DV that decides how long a truck charges, t_i, the subscript c is added, to indicate with what speed has been charged.

Proposition 1. *By introducing multiple charging speeds, $\mathcal{C}_s = \{c_{s_0}, c_{s_1}, ..., c_{s_n}\}$, where $c_{s_0}, c_{s_1} > ... > c_{s_n}$ with corresponding charging costs per kWh, $C_c = \{c_0, c_1, .., c_n\}$, where $c_0 > c_1 > ... > c_n$, the electricity costs of an optimal schedule, can only decrease or stay equal compared to a case where only c_{s_0} with costs c_0 are allowed,*

$$t_{i_0} \cdot c_{s_0} \cdot c_0 \geq t_{i_c} \cdot c_{s_c} \cdot c_c. \tag{3.15}$$

Proof. Trivial, as the amount of electricity that needs to be charged and the time that is available to charge, is the same for both cases. If time allows, a truck may charge with a slower speed. Due to the monotonicity of $\mathcal{C}_s$ and C_c, the total charging costs of the optimal schedule remain equal or reduce if more charging speeds are available. ■

The objective function needs to be adjusted as the electricity costs per minute is not constant. The objective function as described by Eq. 3.2 is replaced by,

$$\text{Minimize} \quad \sum_{\substack{i \in I \\ c \in \mathcal{C}_s \\ k \in K}} x_{i,d_c,k} \cdot t_{i_c} \cdot C_c, \tag{3.16}$$

where C_c is the electricity costs per minute for the charging speed c. The implementation of these new DVs, requires adjustment of the time and load constraints concerning the depot, i.e. Eq. 3.9 and Eq. 3.12. Here, the subscript, c, of d_c needs to be added. Eq. 3.9 is changed to,

$$s_j \geq s_i + t_{i,d_c,k} + t_{d_c,j,k} + t_{i_c}, \quad \text{if } x_{i,d_c,k} = 1 \wedge x_{d,j,k} = 1,\ \forall i,j \in I,\ t_j^a > t_i^a,\ \forall k \in K,\ \forall c \in \mathcal{C}_s \tag{3.17}$$

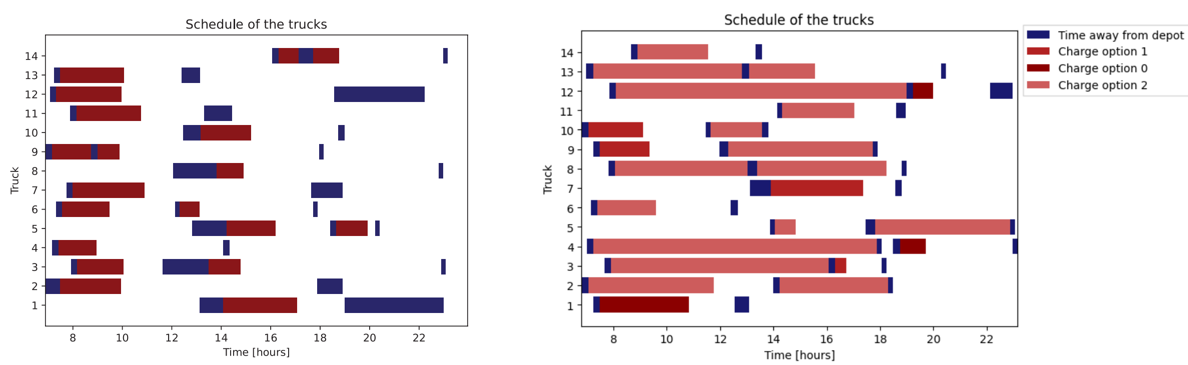
Eq. 3.12 is adjusted in the same way to,

$$q_j \leq q_i - q_{i,d_c,k} - q_{d_c,j,k} + c \cdot t_{i_c}, \quad \text{if } x_{i,d,k} = 1 \wedge x_{d,j,k} = 1,\ \forall i,j \in I,\ t_j^a > t_i^a,\ \forall k \in K,\ \forall c \in \mathcal{C}_s. \tag{3.18}$$

Here it must be noted that $t_{i,d_c,k}$ is the same for all c, as the time it takes to go to the depot to charge with a different speed, does not differ. The same holds for $t_{d_c,j,k}$, $q_{i,d_c,k}$, and $q_{d_c,j,k}$. For this study, we choose to implement 3 different charging speeds. Tab. 3.1 shows an overview of the charging speeds and the costs per minute. As electricity price agreements are made by airports with electricity companies, it is unknown what the costs of electricity are. So the electricity prices, presented in Tab. 3.1 are hypothetical. We assume, that the costs of slow charging per kWh are less than the costs per kWh when charging at a higher speed. So we expect that the electricity costs will decrease and that trucks will be assigned to go to the depot to charge with a slow speed when time allows it.

Charging speed option	**Fully charged in [hours]**	**Ratio**	**Charging costs [€/min]**
0	4	1/1	1
1	8	1/2	0.43 (= 1/2.3)
2	20	1/5	0.0182 (=1/55)

Table 3.1: Overview of the different charging speeds and corresponding costs per minute.



(a) **(b)**

Figure 3.4: A truck schedule of a fleet of 14 homogeneous trucks for a flight schedule of 50 flights on day 2, where 5 minutes of service time is considered and all trucks have a capacity of 150 kWh. **(a)** one charging speed is used and the total electricity costs are € 4716.54. **(b)** 3 charging speeds are used and the total electricity costs are € 3377.50.

Fig. 3.4a shows the truck schedule for 50 flights on day 2 for 14 homogeneous trucks. Here only the fast charging option could be used. The electricity costs for charging during the day of this truck schedule are € 1356.54. The total electricity costs, including the charging to have fully charged trucks at the beginning of the day, are € 4716.54. Fig. 3.4b shows the truck schedule for the same situation, but now 3 different charging speeds could be used. The electricity costs for charging during the day of this truck schedule are less than the costs of the truck schedule where one charging speed was available. The electricity costs for charging during the day of the truck schedule where 3 charging speeds could be used are € 487.90. When we include the electricity costs to get fully charged trucks at the beginning of the day, where we consider that trucks can be fully charged in 8 hours, the total electricity costs are € 3377.50.

A first point to note is, that these truck schedules are not for a minimum amount of trucks. Here, we minimize the electricity costs of the charging during the day, but the trucks start the day fully charged. So, if many trucks are fully charged in the morning, no truck needs to charge during the day, resulting in no electricity costs due to charging during the day. Sec. 3.6 elaborates on the trade-off between the number of trucks and the associated electricity costs.

Another point that must be noted is that this schedule is not an optimal solution, but a maximum solving time is set. The maximum solving time is 1000 seconds. For example one can see in Fig. 3.4b, that the second time truck 3 charges, it charges with the charging speed of charge option 1, however it had time enough to charge with the charging speed of option 2.

In addition, we see that in the case where multiple charging speeds are allowed, Fig. 3.4b, trucks are usually scheduled to go to a single request and then return to the depot to charge. This can be seen by blue blocks being narrow, while in Fig. 3.4a, there appear more blue blocks that are wider, indicating the truck serves multiple requests consecutively. As the deterministic EVRP minimizes the electricity costs, it is convenient for trucks to spend the most time at the depot charging with the slowest speed. This leads to trucks being scheduled to serve a single request and then return to the depot to charge.

Another point that should be addressed, is the fact that a truck can not adapt its charging speed while charging. So the electricity costs depend on the flight schedule and whether there is enough time to charge with a certain speed. So if there is not enough time between arriving at the depot and the time a truck has to leave to charge with the slowest charging speed, the truck must charge faster. In reality, one would ideally charge partly with the slowest (and thus cheapest) charging speed and partly with a higher charging speed. This is the second extension to the deterministic EVRP presented in Sec. 3.1, that we will elaborate on.

3.5.2 Adapting the Charging Speed While Charging

The second extension to the deterministic EVRP concerns adapting the charging speed while charging at the depot.

Let $t_{i_{c_n}}$ be the time a truck charges after serving request i, with charging speed c, at the n^{th} time it chooses a new charging speed. And let $c_{s_{c_n}}$ be the charging speed a truck charges with after n times adapting its charging speed.

Proposition 2. *By introducing the possibility to adapt the charging speed n times while charging,* $\mathcal{C}_s = \{c_{s_{c_0}}, c_{s_{c_1}}, \cdots, c_{s_{c_n}}\}$*, the total electricity costs of the optimal truck schedule remains the same or decreases.*

Proof. Trivial, as allowing trucks to adapt its charging speed while charging, the average speed at which the truck charged (and the associated electricity costs) is lower than when trucks are not allowed to adapt its charging speed and this average charging speed, is a charging speed that is not part of the charging speed set, $\mathcal{C}_s$. As a result of Proposition 1, the total electricity costs must be equal or go down. ■

Introducing the ability for trucks to charge at multiple speeds during one depot visit, can be done in several ways. For this study, we choose to let trucks adapt their charging speed once while at the depot. The implementation of adapting the charging speeds once is already time-consuming. Here, we like to show the possible functionalities that such models can have. We must note that by increasing the number of times a truck can switch charging speeds and by increasing the number of possible charging speeds, the electricity costs can only go down.

As mentioned, there are several ways in which the adaption of charging speed while charging at the depot can be added to this EVRP. Here we choose to increase the set of charging speeds, $\mathcal{C}_s$. By doing this, one could say we introduce a second depot, where trucks go after they were at the first depot. At the second depot, trucks can again charge by the speeds indicated in Tab. 3.1. The transition from the first to the second depot does not cost any time or electricity. This addition of the second depot requires the following adjustments to the mathematical formulation of the EVRP.

First, we split our set of depots, from the set D to the sets D_1 and D_2. The elements of D_1 are d_0, d_1, d_2. These elements are used to indicate whether a truck goes to the first depot to charge with a certain charging speed option, i.e. 0, 1, 2. The set $D_2 = \{d_3, d_4, d_5\}$. Here the indices 3, 4, 5 represent the charging speeds of charging options 0, 1, 2 respectively, but at the second depot. It may not seem obvious why it is needed to split the set of "depot", but some constraints will include DVs that concern trucks going to the depot, so the first time a truck charges, while other constraints concern leaving the depot and thus the second time that a truck chooses a charging speed.

The set of DVs, $x_{i,j,k}$ and t_{i_c} becomes larger as the set $\mathcal{C}_s$ doubles. The notation of the objective stated in Eq. 3.16 does not change, only the set $\mathcal{C}_s$ becomes larger, which affects the total objective but the notation does not change. However, many constraints must be slightly adjusted in notation. The constraints of Eq. 3.3 must be adjusted, one must not sum now over the x -DVs, where the second index belongs to D_2,

$$\sum_{\substack{j \in I \cup D_1 \\ k \in K}} x_{i,j,k} = 1, \quad \forall i \in I. \tag{3.19}$$

The constraints of Eq. 3.4 are slightly adjusted. In the first term, the sum over $i \in I \cup D$, must be replaced by a sum over $i \in I \cup D_2$, while the second sum must become $i \in I \cup D_1$. In addition, we must add a constraint ensuring that trucks always travel from depot 1 to depot 2. If we do not add this constraint, trucks cannot leave the depot, as a result of the adjustment. The added constraints are is,

$$\sum_{j \in D_1} x_{i,j,k} - \sum_{j \in D_2} x_{i,j,k} = 0, \quad \forall i \in I, \ \forall k \in K. \tag{3.20}$$

A truck must always "visit" both depots, however, it can charge at one of the depots for 0 minutes, such that it did not adapt its charging speed while charging. Also, a truck can choose the same charging speed at both depots, such that the charging speed is not adjusted, but the truck did "visit" both depots. The constraints of Eq. 3.5 are adjusted such that in the first term is summed over all elements from the set D_2 and in the second term is summed over the elements from the set D_1,

$$\sum_{\substack{i \in I \\ j \in D_2}} x_{j,i,k} - \sum_{\substack{i \in I \\ j \in D_1}} x_{i,j,k} = 0, \quad \forall k \in K. \tag{3.21}$$

Similar adjustments are done for the constraints of Eq. 3.6, Eq. 3.8, and Eq. 3.12.

Fig. 3.5 shows the truck schedule when allowing trucks to adapt their charging speed once while charging. This is a schedule of 14 trucks that serve 50 flights during one day. The electricity costs due to the charging during the day are € 259.72. The total electricity costs, including the electricity costs to get fully charged trucks at the beginning of the day, are € 3148.60. Fig. 3.4b shows the truck schedule for the same flight schedule, but trucks were not able to adapt their charging speed while charging. The costs of this schedule are € 3377.50. This shows that by allowing trucks to adapt their charging speed, the total electricity costs reduce. It must be noted that these schedules are not optimal, but were limited to a maximum time of solving, namely 1000 seconds. But what is clear, that allowing trucks to adapt their charging speed reduces the electricity costs, as trucks can charge with the slowest speed and thus with the lowest costs and charge for a short amount of time with a higher charging speed if needed. In the case where trucks could not adapt their charging speed, the speed at which a truck charges and thus also the electricity costs involved were dependent on the time in between 2 consecutive tows. When a truck can adapt its charging speed, trucks use the time in between consecutive tows to charge with the slowest charging speed.

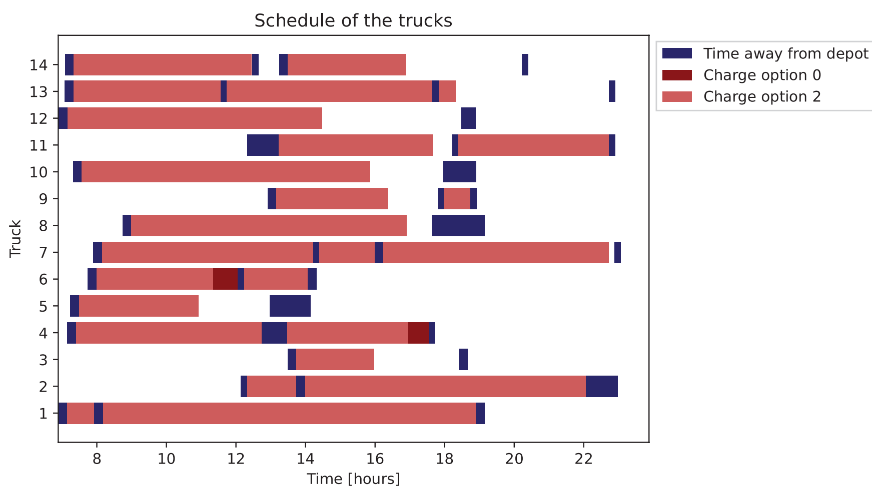


Figure 3.5: The truck schedule of a truck fleet of 14 homogeneous trucks for a flight schedule of 50 flights with a service time of 5 minutes and a truck capacity of 150 kWh. Here trucks could switch from charging speed once while charging at the depot. The total electricity costs are € 3148.60.

3.5.3 Truck and Aircraft Size Categorization

The last extension to the deterministic EVRP is the addition of different trucks and different types of aircraft. One can imagine that an Airbus A380 must be towed by a larger truck than a B737. Or to put it differently, a B737 may be towed by a large truck, but a smaller truck can also tow it. While an Airbus A380 can only be towed by a large truck. In Appendix A an overview of the different aircraft categories and some examples of aircraft of each category are given in Tab. A.1. Adding these constraints can be done by introducing 2 new parameters: the truck category, c_k^t of truck k and aircraft category, c_i^r of request i. For now, we categorize the trucks and aircraft into 3 categories. The trucks differ in capacity and the electricity needed to tow the different sized aircraft for the different tasks is given in Tab. A.3. The electricity needed for all different categorized aircraft is implemented in the parameter $q_{i,j,k}$, which indicates the amount of electricity associated with the DV $x_{i,j,k}$.

The constraints that are added to ensure that aircraft are towed by a truck that can tow it, is,

$$\sum_{j \in I \cup D_1} x_{i,j,k} \cdot (c_k^t - c_i^r) \geq 0, \quad \forall i \in I, \ \forall k \in K. \tag{3.22}$$

In the case that $x_{i,j,k} = 1$, the truck category of truck k, c_k^t, must be larger or equal to the aircraft category of request i, c_i^r. In the case that $x_{i,j,k} = 0$, the truck and aircraft category do not matter.

These constraints are implemented to the EVRP. As stated in Appendix A, more electricity is needed to tow larger-sized aircraft. This way, the total electricity needed increases when large aircraft need to be towed, compared to the case where only small aircraft need to be towed. This has an impact on the feasibility and total electricity costs of the truck schedule. As this is highly dependent on the parameters set, it is difficult to make a good comparison with the results presented in this chapter, such that we leave it out.

3.6 Number of Trucks versus Electricity Costs

As mentioned before, it is a trade-off between how many trucks are used and the electricity costs of the truck schedule. Especially when airports need to chance their total Ground Service Equipment (GSE) fleet, Ground Service Handlers (GSH) need to answer the question, how many trucks need to be bought? We determine the total electricity costs of different numbers of trucks that serve all requests of the same flight schedule. Fig. 3.6 shows the total electricity costs for a flight schedule of 36 flights for different fleet sizes, where we consider 8 minutes of service time. Here, we consider all trucks and aircraft to be of the same category. The trucks may charge with different charging speeds and may adapt their charging speed once while charging. In addition, we subtract the electricity costs of all electricity that is not used by trucks. So all trucks will be empty at the end of the day.

It can be seen that a fleet size of 13 trucks results in the lowest total electricity costs. This is due to the fact that the trucks of a fleet of 12 trucks need to charge a significant amount of time during the day with the charging option 0. This results in the electricity costs due to charging during the day being significantly higher. At least 11 trucks are needed to serve all aircraft on time. The truck schedule of the fleet of 17 trucks results in a schedule where trucks only need to charge during the day with charging speed option 2. Note, that the trucks charge with charging speed 1 at night. The truck schedule of 16 trucks results in fewer total electricity costs, as during the day more time can be charged with charging speed 2 compared to the schedule of 17 trucks, and the model is still feasible.

These calculations have been done for many different fleet sizes and for different flight schedules. All results show similar behavior, the costs decrease when fewer trucks are available, up till the point that the trucks of the fleet have to charge for a significant amount of time with the charging speed of option 0, resulting in the total electricity costs to increase, when fewer trucks are available. In addition, there is a minimum amount of trucks needed to serve all aircraft, a fleet of fewer trucks results in the EVRP to be infeasible and all requests can not be served on time, or there is not enough time to charge during the day.

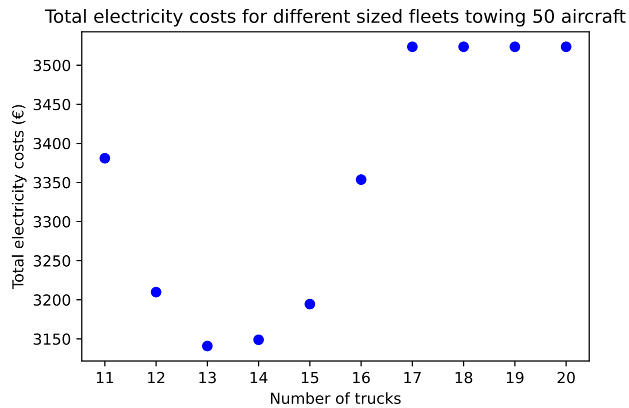


Figure 3.6: The total electricity costs of the best-found solution of the deterministic EVRP of different sized truck fleets that serve a flight schedule of 36 flights.

3.7 Comparison with a VRP of Non-Electric Towing Trucks

To show the versatility of our EVRP and to compare the case of electric trucks with that of trucks that do not need to be charged, we present a truck schedule of a VRP of non-electric trucks.

The deterministic EVRP presented in Sec. 3.1 is adjusted to create a VRP of non-electric trucks. Two main adjustments are done. Firstly, the objective of the VRP cannot be to minimize the electricity costs as the trucks do not have to charge. The objective function of the VRP is to minimize the total driving time. Secondly, all constraints regarding the battery levels of trucks are removed, i.e. all constraints of Sec. 3.1.7. Here we do not consider that it takes time to fill a truck with diesel (or another type of fuel). We assume that these non-electric trucks drive at the same speed as the electric trucks considered before. Also, the same service times are considered. Fig. 3.7 shows the truck schedule of 3 non-electric trucks, that serve 50 flights of day 1 of the considered flight schedule. The minimum amount of trucks needed to serve all 50 flights on time is 3. In Sec. 3.4, we presented the best-found solution of the deterministic EVRP of 50 flights. For the EVRP the minimal amount of trucks needed to serve 50 flights at day 1 is 11 trucks. So for the EVRP significantly more trucks are needed to tow all aircraft on time. This is due to the fact that the electric trucks of the EVRP need to charge, while the non-electric trucks of the VRP do not have to charge.

Another point that should be addressed, is that for this VRP an optimal solution is found within the maximum solving time, while for the EVRP only a best-found solution was found within the maximum solving time. In addition, it must be noted that this VRP solves, in comparison to the EVRP, very fast: the optimal truck schedule of Fig. 3.7, was found in 3 seconds, while the best-found solution of a EVRP of 50 flights and 11 trucks was found in 1000 seconds. It must be noted that the reason why the VRP solves so fast is not due to the fact that the minimum amount of trucks needed for the VRP, is so low. For small systems (4 electric trucks and 12 aircraft), no solution with an optimality gap of 0, was found within a few minutes of the EVRP.

This result shows the main difference between a VRP and our formulated EVRP. It shows that our EVRP is computationally more "complex" than a VRP. This brings us to the question, what defines the complexity of a MILP? In literature, there is no consensus on what defines the complexity in terms of the solving time of a MILP [54–56], as this is highly dependent on the input parameters of the objective and the constraints.

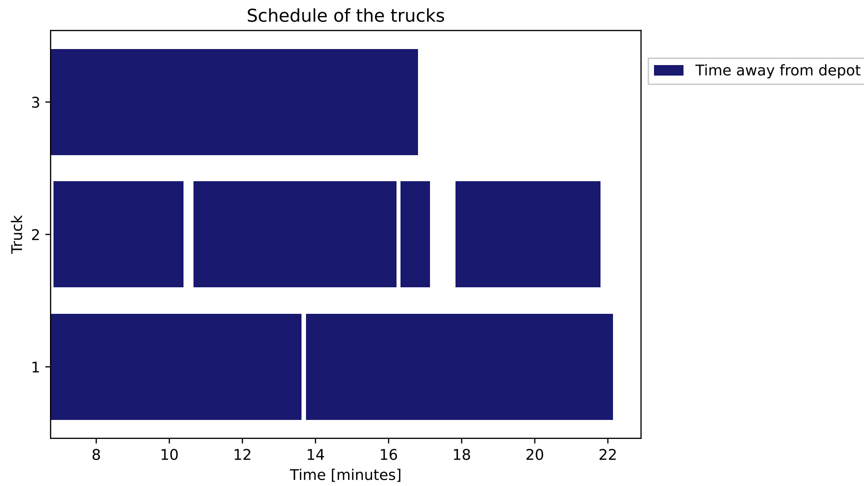


Figure 3.7: Truck schedule of 3 non-electric trucks serving 50 flights. The total driving time is 39328 minutes.

However, we can state some qualitative observations. In Tab. 3.2, we compare the number of constraints and (binary) DVs of the VRP and the EVRP for large and smaller systems. The number of continuous DVs of the EVRP is 8 times that of the VRP. This is because the VRP does not contain the DVs q_i and $t_{i_{c_n}}$. In addition, the constraints that the EVRP has, which the VRP does not have, are constraints that make the DVs dependent. As a decision to go to the depot to charge for an EVRP, influences the level of the battery load, but also which request it can serve at a later moment in time. This is not the case for the VRP. For the VRP whether a truck goes to a certain request, depends on whether the truck can be there on time. For the EVRP this also depends on whether a truck's battery is full enough and whether it has enough time to charge during the day. For example, the constraints of Eq. 3.18 are part of the EVRP, but not of the VRP. This set of constraints contains the DVs q_i, q_j, $t_{i_{c_n}}$, $x_{i,d,k}$, and $x_{d,j,k}$. So the constraints that are added to the EVRP compared to the VRP, make the DVs dependent and thus results in a computationally more complex problem.

Number of:	**5 Trucks, 16 flights**		**14 Trucks, 50 flights**	
	EVRP	**VRP**	**EVRP**	**VRP**
Constraints (rows)	7 380	1 259	193 835	25 603
Columns	1 064	862	13 911	10 355
Non-zero elements	55 213	14 063	1 524 155	353 685
Continuous DVs	128	16	400	50
Binary DVs	935	845	13 510	10 304

Table 3.2: Comparison of the model characteristics of the VRP as introduced in this section and the EVRP as introduced in Sec. 3.5. Here the number of rows and columns correspond to the number of rows and columns of matrix A, of each MILP of the (E)VRP, as defined in the definition of a MILP in Def. 2.2.1. The number of non-zero elements corresponds to the non-zero elements of matrix A.

3.8 Conclusions on the Deterministic EVRP

In conclusion, we have formulated a deterministic Electric Vehicle Routing Problem (EVRP) as a Mixed Integer Linear Program (MILP) that describes the operations of electric towing trucks at an airport of a deterministic flight schedule, minimizing the electricity costs. This way, we accomplished one of our research goals as stated in Sec. 1.4.3. Due to the computational complexity of solving this MILP, a maximum solving time is set and a best-found solution of the MILP is found. From this best-found solution, the routes of the electric trucks of a fleet that tow all aircraft on time from the gate (landing lane) to the runway (gate) of departing (arriving) aircraft of a certain flight schedule at an airport, can be derived. In addition, from the best-found solution can be derived when each truck must charge for how long and at what charging speed it must charge.

In addition, we found that, by allowing trucks to charge at different speeds and adapting the charging speed while charging, the total electricity costs reduce. This extension is added to the EVRP description, by adding multiple depots where trucks can charge at each depot with a different charging speed. Going from a depot to another does not cost electricity or time. Lastly, we found that describing the operations of non-electric towing trucks by a Vehicle Routing Problem (VRP) is significantly less computational complex to solve. This emphasizes the computational complexity of an EVRP compared to a VRP.

Chapter 4

Robust Optimization

Aircraft may be delayed or arrive early due to all kinds of reasons. The moment in time an aircraft needs to be towed is thus uncertain and this may change the optimal operations of the electric trucks significantly. We introduce two methods to take account of the uncertainty in arrival and departure times of aircraft. In this chapter, we present the first method. In this chapter, we present how the operations of electric towing trucks at an airport may be optimized under the uncertainty of the arrival and departure times of aircraft, by Robust Optimization (RO). In Chap. 5, we present the second method, which uses a dynamic approach to determine the operations of a fleet of electric towing trucks under uncertain arrival and departure times of aircraft.

Different types of stochastic optimization could be suitable to describe the electric towing trucks' operations under uncertain arrival and departure times of the aircraft. In this chapter, we show that RO is a suitable approach. However, there are multiple suitable candidates and in Appendix. D, we discuss how *Stochastic Programming* (SP) could be used to describe the operations of electric towing trucks at an airport under uncertain arrival and departure times and we show that a RO-approach and a SP approach are very similar.

RO is a field of research that concerns optimization problems in which a certain measure of robustness against uncertainty is sought. Within the field of RO, different techniques may be used for different types of uncertainty problems. Before we motivate why RO is a suitable technique to describe the operations of electric towing trucks at an airport under the uncertainty of arrival and departure times, we must discuss the uncertainty in arrival and departure times in more detail.

4.1 Distribution of the Uncertain Arrival and Departure Times

Delays may be due to various reasons, among many others, weather effects may influence whether an aircraft may arrive or depart (late) and, delay in ground-based activities, e.g. the cleaning or catering process may result in a delay of departing aircraft. It is important to note that the delay of arrival and departure times may differ per airport, per airline, per flight, and per moment in time (day/year). In addition, the delay of aircraft in the morning (may) have an effect on the operations at an airport and possible delay of an aircraft at a later moment that day. So we need to agree on the formulation of the uncertainty in arrival and departure time. However, not a lot of data on arrival and departure delays is published or freely available, as these statistics may harm an airport's reputation. We do not have data on the delays at Rotterdam Airport. For this thesis, we make the assumption that the delay of arrival and departure times are normally distributed. However, in reality, this distribution is not valid for most airports and airlines. We need to emphasize, that if the presented mathematical model of this chapter is used for a specific airport, it is of high importance that the distribution used is a good representation of the uncertainty in arrival and departure times.

Novianingsih *et al.* studied in [57] the delays of Garuda Indonesia Airline and fitted the delays of all arriving and departing aircraft of its aircraft fleet in 2012. They found that the delay of arriving aircraft can be described by a normal distribution, with a mean of -2.73 minutes and a standard deviation of 13.75 minutes, $N(-2.73, 13.75)$. The delay of departing aircraft can be described by a normal distribution, $N(-1.54, 10.49)$. Throughout this thesis, these distributions are used to describe the delay in arrival and departure times at an airport. The effect that delays early on the day may have on flights later that day, is not taken into account in Novianingsihs study and thus also not taken into account in this thesis.

4.2 Robust Optimization Approaches

Now that we stated how the uncertainty of the arrival and departure times is described in this thesis, we can focus on different types of RO and decide on the type that is best suitable to describe the operations of electric towing trucks at an airport under the uncertainty of arriving and departing times of aircraft. Here we discuss 3 important types of RO, namely the approach of Charnes, Cooper *et al.* [58], the approach of Soyster [59], and the approach of Ben-Tal and Nemirovski [60].

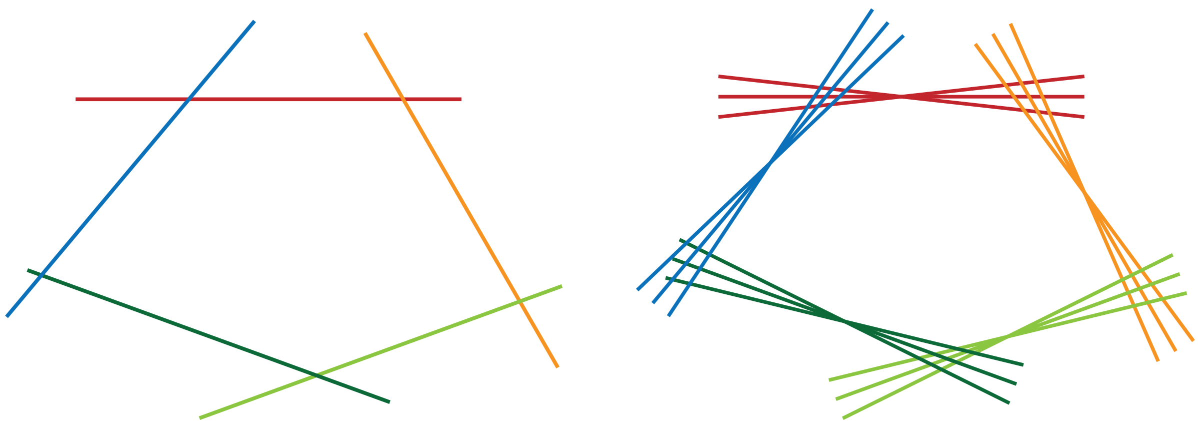
Charnes, Cooper *et al.* are known for their studies on *chance-constrained* problems within the RO research field [58]. Chance-constrained problems are characterized by constraints that need to be satisfied with some probability. For example, a chance-constrained problem may describe the optimal operations of the electric towing trucks under uncertain arrival and departure times, if a percentage of all aircraft need to be served on time. However, this type of RO is not the most suitable, as these constraints constrain that a certain amount of aircraft is towed not on time. This way it must be known with what probability a certain aircraft arrives in time. In this thesis, we consider that the delays can be described by a normal distribution, so this probability can be determined. However, in reality it is difficult to determine this distribution, as it depends on many factors and we expect schedulers to use historic data and sampled scenarios. This way, a chance-constrained description is less suitable than other methods presented in the rest of this section.

Soyster introduced another method to describe optimization problems under uncertainty. [59]. In Def. 2.2.1 we defined matrix A as the matrix that contains all coefficients of the constraints of a Mixed Integer Linear Program (MILP). Let $J_i = \{j : a_{ij} \in A, \text{ subject to uncertainty}\}$. Soyster considers all coefficients of the constraints that are subject to uncertainty, a_{ij}, as symmetric and bounded random variables. This way, each entry $a_{ij}, j \in J_i$ becomes a bounded random variable $\tilde{a}_{i,j}$ in the interval $[a_{i,j} - \tilde{a}_{i,j},\ a_{i,j} + \tilde{a}_{i,j}]$. However, the uncertainty of the arrival and departure times of aircraft are not necessarily a bounded or symmetric random variable. For this thesis, we consider the uncertainty of arrival and departure times to be normally distributed, so not bounded. There are many examples where the uncertainty of arrival and departure times cannot be described by a bounded and symmetric random variable [27–29, 61]. So, if a RO-based uncertain Electric Vehicle Routing Problem (EVRP) is used to describe the operations of electric towing trucks at a specific airport, it is desired not to be bound by the way the delay in arrival and departure times need to be described, as is the case for the Soyster approach where the uncertainty must be described by a bound and symmetric random variable.

Ben-Tal and Nemirovski introduced in 1999 [60] a way to describe an optimization problem under uncertainty, where the uncertainty may be described by an unbounded distribution. In addition, the method of Ben-Tal *et al.*, allow scenario-based optimization instead of describing the uncertainty by a known distribution. This method is known as the *min-max robust approach*. The idea of this approach is to determine the solution which is feasible in all sampled scenarios and optimal in the worst case. These scenarios can be sampled from a known distribution or based on historic data. Rewriting the definition of a MILP into its robust counterpart,

$$\begin{aligned} \min_{x} \quad \max_{j \in E} \quad & f_j^T x \\ \text{s.t.} \quad & a_j x \leq b_j, \quad \forall j \in E \\ & x_i \in \mathbb{Z}, \quad \forall i \in I. \end{aligned} \tag{4.1}$$

Here E is the set of sampled realizations of the uncertain parameters. The number of sampled realizations must be sufficiently large. However, in the case of uncertainty in arrival and departure times, it is not directly clear whether a specific delay or early arrival/departure is beneficial or detrimental to the objective function. So it is difficult to determine what the sampled realization of the flight schedule is, that is the worst-case. In the next sections, we discuss how this is bypassed for our description of an EVRP.



(a) (b)

Figure 4.1: Schematic representation of a feasible set of an optimization problem without **(a)** and with **(b)** uncertainty.

4.3 An EVRP under Uncertainty using a Min-Max RO-Approach

As the EVRP, as explained in Chap. 3 only has hard constraints, for the RO-based model, we want all constraints to be met for many realizations of the flight schedule. So the question is, what are the optimal operations such that for a large number of possible realizations of a flight schedule, all aircraft will be served on time? This can be done by sampling flight schedules using the distribution of the delay and adding the time-window constraints of all requests by the sampled realizations to the deterministic EVRP as presented in Chap. 3. Fig. 4.1a schematically depicts the set of feasible solutions in the case that no uncertainty is present, like the deterministic EVRP presented in Chap. 3. Fig. 4.1b schematically shows what happens when 3 samples of a flight schedule are sampled and the corresponding time-window constraints of all requests are added. One can see that by adding constraints the set of feasible solutions gets smaller. By adding these constraints, the EVRP may become infeasible and more trucks are needed to tow the aircraft within the time-windows of all sampled arrival/departure times.

This method of adding extra time-window constraints to the deterministic EVRP as a RO-approach, looks like the min-max robust approach of Ben-Tal *et al.*, but we do not specifically determine the worst-case sampled scenario (flight schedule). Determining the worst-case sampled scenario is not trivial, as an early arrival of an aircraft may be beneficial but also detrimental to the truck schedule. So it is difficult to say whether a sampled scenario is a worst-case scenario. Instead, we minimize the electricity costs considering all sampled flight schedules. By sampling more flight schedules, the probability that all aircraft are towed on time for the actual realization of the flight schedule, increases. However, there will be a probability that not all aircraft can be towed on time for the realization of the flight schedule. In Sec. 4.4, we motivate how many samples of the flight schedule we used and what the probability is that the realization of the flight schedule results in not all aircraft being towed on time. We denote the n^{th} sampled arrival/departure time of request i, by $\tilde{t}_i^n$.

Before we present the results on our EVRP under uncertain arrival and departure times using a RO-approach, we must clarify two last points, namely (1) what do we consider as the moment in time the truck must be at the start location of the tow, as the moment in time an aircraft arrives is uncertain and thus also the moment in time the truck starts a tow is uncertain and (2) what we consider as the moment in time that a truck is actually finished with the tow, as the starting time is uncertain and thus also the moment in time the truck finished a tow. These two points are discussed in the next sections.

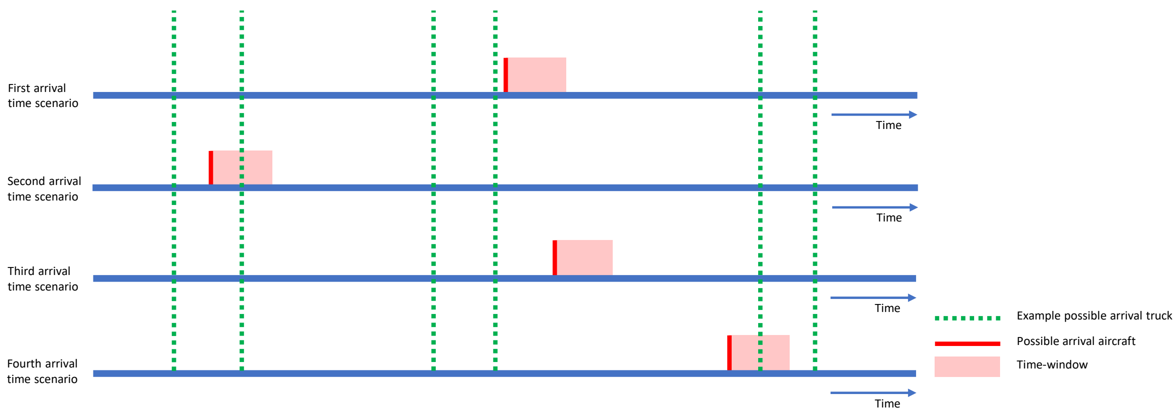


Figure 4.2: Schematic representation of deciding when a truck must be present at the start location of a tow by sampled realizations of the actual arrival/departure time of an aircraft. The 4 red lines on the different timelines show possible sampled arrival times of a single request. The green dotted lines show possible moments in time that a truck must be present at the start location of a tow. The pink areas are the time-windows in which the aircraft needs to be towed as described for the deterministic EVRP of Chap. 3. It can be seen that there is no moment in time where a truck can start to tow the aircraft of this request, where it is in the time-windows of all sampled realizations of the arrival time of the aircraft.

4.3.1 The Time a Truck Needs to be Present at the Tow Location

In this section we discuss the first point that needs clarification. Fig. 4.2 schematically depicts 4 possible sampled arrival times of a certain request, indicated by the 4 red lines on the timelines. The 3 green dotted lines indicate examples of possible start times of the tow, which still needs to be decided on. The pink areas represent the time-windows as they are introduced in Chap. 3. Namely, as a time-window (of 5 minutes) after an aircraft arrives/departs. However, it can be seen that if we do not change the time-window in which a truck is allowed to start to tow the aircraft, there is not a moment in time a truck can start to tow within the time-windows of all sampled arrivals of the aircraft, as the there is no moment in time on the timeline, the dotted green line can go through the pink areas of all sampled arrival times.

But what we do know, is that we want to have a truck at the start location of the tow at the earliest sampled realization of the arrival/departure time of an aircraft. We ensure that a truck is present at the start location of the tow before the end of the time-window of the earliest sampled realization of each request i, we replace the set of time-window constraints of Eq. 3.7 of the deterministic EVRP described in Chap. 3 by,

$$s_i \leq \min_n \tilde{t}_i^n + 5, \quad \forall i \tag{4.2}$$

So the time-window constraint is now replaced by a constraint, constraining a truck to be present at the start location of the tow before the end of the time-window of the earliest sampled realization of the arrival/departure of request i. This is schematically depicted by Fig. 4.3.

Figure 4.3: Schematic representation of the time the truck may arrive latest at the start location of the tow for a specific request, where the sampled arrival times of this request are depicted by the red lines. The green line is the moment in time the truck may arrive latest at the start location of the tow. And the pink area is the time-window of the earliest sampled arrival time of a request.

4.3.2 The End Time of a Tow

This leads to our second point that needs clarification, namely, what do we consider as the moment in time the truck is finished with the tow, such that it can be scheduled to go to another tow or return to the depot. In our deterministic EVRP of Chap. 3, it is considered that the truck starts to tow when it arrives at the start location of the tow, or in case that the aircraft is not there yet, a truck starts to tow when the aircraft arrives. Now for the case that the arrival and departure times are uncertain, the truck is assigned to be at the start location of the tow no later than the end of the time-window of the earliest sampled arrival/departure time of the tow. However, now it is uncertain when the aircraft arrives, so we cannot state that a truck starts to tow when it arrives at the start location of the tow, as the aircraft may not have arrived. So it is unknown when a truck finishes a tow and is ready to tow another aircraft or return to the depot (to charge).

This is schematically depicted in Fig. 4.4. In this figure, again 4 possible arrival times are depicted. We consider that a truck is present no later than the end of the time-window of the earliest sampled arrival/departure time of this aircraft, indicated by the solid green line. The shaded green areas indicate the time that a truck cannot be assigned to go to another request or return to the depot, for each sampled realization of the arrival/departure time. It can be seen that the moment in time that a truck can be assigned to go to another request or return to the depot is uncertain and differs per sampled realization of the arrival/departure time, indicated by the green dotted lines.

For the EVRP with uncertain arrival and departure time, described by a RO-approach, we consider that a truck tows an aircraft when the aircraft arrives and we set a maximum to the time that a truck may wait for an aircraft to arrive/depart. We consider 2 potential options for this maximum time that a truck may wait for an aircraft to be towed:

Option 1 Mean of the sampled realizations of each request i, $\tilde{t}_i^{\text{mean}}$, indicated by the pink dotted line in Fig. 4.4

Option 2 Maximum of the sampled realizations of each request $\tilde{t}_i^{\text{max}}$, indicated by the blue dotted line in Fig. 4.4

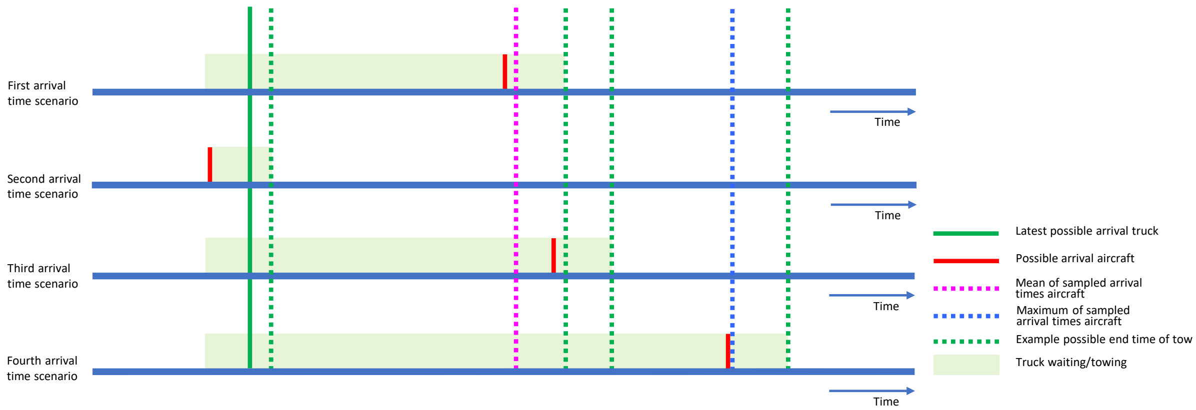


Figure 4.4: Schematic representation of deciding when a truck may be scheduled to go to another request or return to the depot. The 4 red lines on the different timelines show possible sampled arrival times of a single request. The green solid line shows the latest moment in time a truck must be present at the start location of the tow. The green shaded areas are the time-windows in which a truck cannot be assigned to go to another request or return to the depot. The dotted green lines are examples of the moment in time a truck might be done for each sampled realization of the arrival time. The dotted pink line indicates the mean of the sampled arrival times of the request and the dotted blue line indicates the maximum of the sampled arrival times of this request.

Both options have their disadvantages. In the case of option 1, an aircraft may not have arrived yet, when a truck is considered to start with the tow. Aircraft that arrive later than the mean of the sampled realizations are not towed. So this option is not a realistic representation of reality, as aircraft might be left behind. However, we would like to see what the effect of the uncertainty in arrival and departure times is. So this option is studied in order to compare with option 2. In option 2, we demand trucks to wait until the latest sampled arrival/departure time, so all aircraft of the sampled scenarios have arrived within the time the truck has to wait for an aircraft to arrive/depart. So, if the realization of the arrival of the aircraft is within the earliest and latest sampled scenario, the aircraft is towed on time in reality. But a truck may need to wait (unnecessary) long after they towed the aircraft to go to another tow or to return to the depot, as a truck cannot be scheduled in advance to go to another request or to the depot before the maximum sampled arrival/departure time of the request. And as the standard deviation of the delay in arrival and departure times are respectively 13.75 minutes and 10.49 minutes, this waiting time may be long. But option 2 will result in aircraft of which the actual arrival/departure time is between the earliest and latest sampled arrival/departure time of the request, being towed on time, while the arrival and departure times are uncertain.

This adjustment concerning the moment in time, a truck actually is done with a tow results in the adaption of 2 sets of constraints of the deterministic EVRP as described in Chap. 3, namely the set of constraints of Eq. 3.8 and of Eq. 3.9. In the case that we consider the latest moment in time a truck starts to tow to be the mean of the sampled arrival times of an aircraft, Eq. 3.8 is adjusted to,

$$s_j \geq \tilde{t}_i^{\text{mean}} + t_{i,j,k}, \quad \text{if } x_{i,j,k} = 1,\ \forall i, j \in I,\ i \neq j,\ \forall k \in K \tag{4.3}$$

And Eq. 3.9 is adjusted to,

$$s_j \geq \tilde{t}_i^{\text{mean}} + t_{i,d,k} + t_{d,j,k} + t_i, \quad \text{if } x_{i,d,k} = 1 \wedge x_{d,j,k} = 1,\ \forall i, j \in I,\ t_j^{a,d} > t_i^{a,d},\ \forall k \in K. \tag{4.4}$$

Likewise, for the case where we consider that the maximum start time of a tow is the maximum sampled arrival/departure time of a request, $\tilde{t}_i^{\text{mean}}$ in Eq. 4.3 and in Eq. 4.4, is replaced by $\tilde{t}_i^{\text{max}}$.

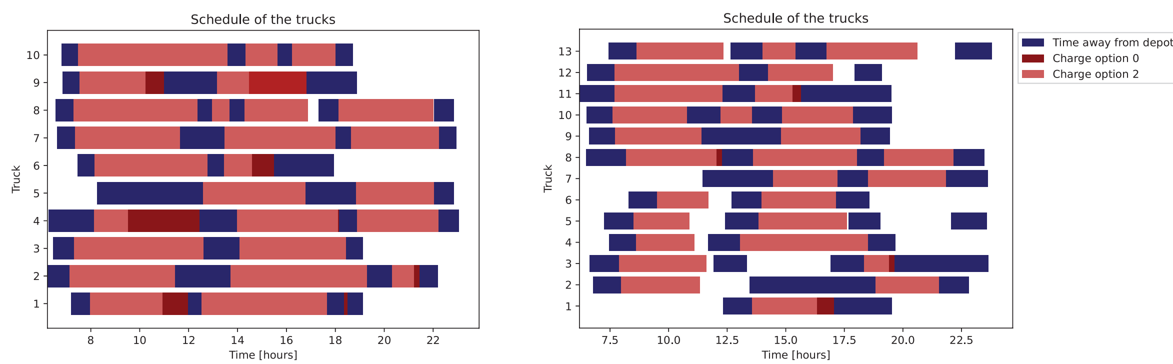
4.4 Results of an Uncertain EVRP using a RO-approach

In this section we present and discuss best-found solutions of the EVRP, that describes the operations of electric towing trucks at an airport under uncertain arrival and departure times, using a RO-approach. For all results of the RO-based models presented throughout this thesis, we sample 300 arrival/departing delays for every request. To indicate that 300 samples is enough, we sampled for 1000 days 300 flight schedules of 50 flights and we determined for every request what the earliest sampled arrival/departure is. From these earliest sampled arrival/departures, we determined which earliest sample was closest to the scheduled arrival/departure. Or to put it differently, we determined for 1000 days, which is the sample that has the highest probability of a truck not being present on time to tow an aircraft, when we demand a truck to be there no later than the earliest sampled arrival/departure time (+ 5 minutes). One time sampling for 1000 days, shows that the highest probability over 1000 days, that a truck is not on time to tow an aircraft of the sampled scenarios is, 0.017. So over 1000 days, in the worst-case, there is a single aircraft where the probability is 0.017 that a truck is not present on time. We consider this probability low enough, such that we consider 300 samples as enough samples.

Fig. 4.5a shows the truck schedule of the best-found solution of an uncertain flight schedule of 50 flights of day 2, where trucks were considered to wait for an aircraft to arrive/depart until the mean of the sampled arrival/departure times of each request (option 1). Remember that we defined the best-found solution in Sec. 2.3 as the feasible solution that has the minimal objective unction value, that is found within the maximum solving time. The maximum solving time is set to 1000 seconds. 300 arrival/departure times are sampled for each request from the distributions discussed in Sec. 4.1. A minimum number of 10 trucks are needed to serve all aircraft on time. The electricity costs due to charging during the day are € 1049.20. The total electricity costs, including the electricity costs due to the charging of the trucks such that they are fully charged at the beginning of the day, are € 3109.20. As this schedule is made at the beginning of the day, trucks will follow this schedule. So the realization of the actual flight schedule will not affect the total electricity costs. So the realization of the flight schedule may only result in an aircraft not being towed, if it arrives before the earliest sampled arrival time like discussed in the previous section.

In Sec. 3.4, we discussed the truck schedule of 50 flights of day 2, where the flight schedule is considered deterministic. Fig. 3.3 shows this truck schedule. For the deterministic case, a minimum of 9 trucks was needed to tow all aircraft on time. Here, we see that the minimum amount of trucks to serve all aircraft on time for an uncertain flight schedule, where trucks are considered to start the tow of each request at the mean of the sampled arrival/departure times, is 10. An overview of these results is shown in Fig. 4.6. In addition, we see that indeed trucks take longer for each tow, as the blue blocks in Fig. 4.5a are wider than in Fig. 3.3, on the trips that a truck tows a single request. For example, during the first trip of truck 1 of the truck schedule of Fig. 4.5a, this truck tows a single truck. This is wider than the blue block of the first trip of the second truck of the truck schedule of Fig. 3.3, where truck 2 also tows a single truck during that trip. This is as expected, as trucks need to be on time for the earliest sampled arrival/departure time of each request, but cannot be scheduled for another tow or scheduled to return to the depot until the mean of the sampled arrival/departure times of the request.

However, option 1 is not a realistic representation, as many aircraft may not be towed. Option 2 results in a low probability that an aircraft is left untowed. We have performed 12 runs for the option 2 case. For every run, different arrival/departing delays are sampled per request, and thus a different truck schedule is determined by the model. It was found that 9 out of these 12 runs resulted in a feasible model. Here, we only present the results of the first run. The results of the other runs are presented in Appendix E.



(a) **(b)**

Figure 4.5: Truck schedule of a fleet of 10 (13) trucks of a flight schedule of 50 flights, determined by a RO-approach, where trucks could leave for another tow after the mean (maximum) of the sampled request times. **(a)** Truck schedule of uncertain arrival and departure times, where trucks were allowed to leave after the mean of the sampled arrival/departure times over 300 samples of each request (option 1). Here 10 trucks were needed for 50 flights and the total electricity costs are € 3109.20. **(b)** Truck schedule of uncertain arrival and departure times, where trucks were allowed to leave after the maximum sampled arrival/departure times over 300 samples of each request. Here a minimum of 13 trucks was needed for 50 flights and the total electricity costs are € 2964.53.

Fig. 4.5b shows the truck schedule of the best-found solution of the EVRP with uncertain arrival and departure times, described by a RO-approach, of 50 flights on day 2, where trucks are considered to wait until the latest sampled arrival/departure time (option 2). The minimum number of trucks needed to serve all aircraft on time is 13. The maximum solving time is set at 1000 seconds and 300 arrival/departure times are sampled for each request. The electricity costs due to charging during the day are € 280.53 and the total electricity costs are €2964.53. The time that is scheduled for trucks to serve an aircraft is longer, resulting in more trucks are needed to serve all aircraft on time, compared to the case where trucks are considered to start a tow at the mean of the sampled arrival/departure times. This can be seen by the blue blocks being wider in Fig. 4.5b than in Fig. 4.5a on trips where a single aircraft is towed during a trip. In both Fig. 4.5a and in Fig. 4.5b, truck 1 tows a single truck during the first trip of the day.

In addition, the electricity costs due to charging during the day of the truck schedule of Fig. 4.5b is less than the electricity costs of the truck schedule of Fig. 4.5a, as more trucks are needed to serve all aircraft in the case that trucks are considered to start the tow at the maximum sampled arrival/departure time. As we assume all trucks to be fully charged at the beginning of the day, trucks need to charge less in the truck schedule of Fig. 4.5b than in that of Fig. 4.5a. Comparing the total electricity costs, we saw that the total electricity costs of the truck schedule of Fig. 4.5a are € 3109.20, while the total electricity costs of the truck schedule of option 2, Fig. 4.5b are € 2964.53. This results in lower electricity costs of the truck schedule of Fig. 4.5b compared to the truck schedule of Fig. 4.5a. This is due to the fact that the trucks of the truck schedule of Fig. 4.5b need to charge less time with the charging option 0, than the trucks of the truck schedule of Fig. 4.5a.

In reality, all aircraft need to be served on time, so the truck schedule of Fig. 4.5a where trucks are considered to start a tow no later than the mean of the sampled arrival/departure times is not a realistic representation. However, we see that only 1 truck more is needed for this case (option 1), compared to the deterministic case as discussed in Chap. 3. While for the EVRP with uncertain arrival and departure times, where trucks are not

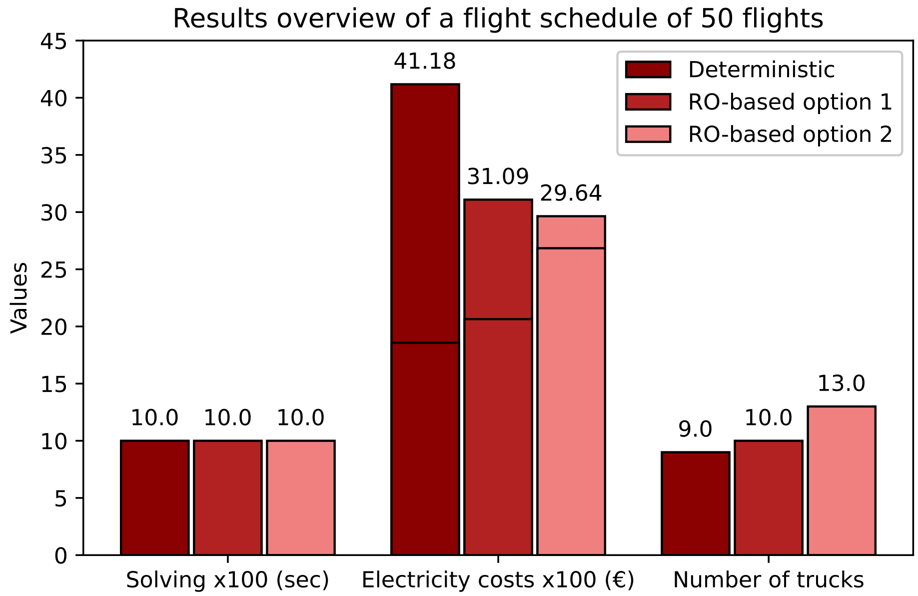


Figure 4.6: Comparison of the results of the deterministic model and the RO-based models where 50 aircraft had to be towed. The electricity costs due to the charging during the day and due to the charging of the trucks to get them fully charged at the beginning of the day are separated in this graph by a line. The top part of the bar indicates the electricity costs due to the charging during the day.

scheduled to go to another request or to return to the depot until the latest sampled arrival/departure time (option 2), 13 trucks were needed, this is 4 trucks more compared to the deterministic case and 3 trucks more compared to the case where a truck needs to wait till the mean of the sampled arrival/departure times of a request (option 1). This shows that uncertainty in arrival and departure times has a major impact on the best-found solution of an EVRP where all aircraft of all sampled arrival/departure times need to be towed on time, needs to be valid. An overview of the results of the deterministic and the RO-based models (option 1 and options 2) is presented in Fig. 4.6.

From Fig. 4.6, it can be seen that there is not a difference in solving time set. This is due to the fact that the RO-based models do not contain more constraints than the deterministic models. It might be argued that it is more difficult to find a feasible solution as the set of feasible solutions reduces. However, it is found that this is not significant, such that the maximum solving time set does not need to be increased. The deterministic model results in the highest total electricity costs. However, this is due to the fact that the deterministic model also results to be feasible with the smallest fleet of trucks. The trucks for the deterministic model need to charge a significant amount of time with the charging option 0, so the electricity costs due to charging during the day are relatively high. The total electricity costs of the RO-based models are lower than of the deterministic model, however, it must be emphasized that the RO-based model option 1, is not a realistic option, as aircraft may be left untowed. The RO-based model of option 2 results, most likely in all aircraft being towed on time. However, there are 4 trucks more needed compared to the deterministic model.

4.5 Conclusions on the EVRP under Uncertain Arrival and Departure Times, using a RO-Approach

In conclusion, we have formulated an Electric Vehicle Routing Problem (EVRP) under uncertain arrival and departure times, using a min-max Robust Optimization (RO) approach, that minimizes the electricity costs, while ensuring all aircraft of the sampled arrival/departure times are towed on time. This way, we accomplished our second research goal, as stated in Sec. 1.4.3. The start time of the tow and the moment in time the truck can be assigned to another request or return to the depot, had to be specified, as the arrival/departure time of an aircraft is uncertain. Constraining the Decision Variables (DVs) s_i to be less or equal to the end of the earliest sampled arrival/departure time-window, results in trucks being on time at the start location of the sampled arrival/departure times of a request. By not scheduling a truck to go to another aircraft or to return to the depot, until the latest sampled realization of the arrival/departure time, ensures that all aircraft of the sampled arrival/departure times are towed on time. Sampling 300 arrival/departure times of each request, is considered to be enough. The probability that the actual arrival/departure time is earlier than the earliest sampled arrival/departure time of each request are considered small enough.

It is found that uncertainty in arrival/departure times has a major impact on the truck schedule and more trucks are needed to ensure that aircraft are served on time for the sampled arrival/departure times. Compared to the deterministic EVRP, 4 more trucks were needed to tow 50 aircraft on time for 300 sampled arrival/departure times, for the uncertain EVRP discussed in this chapter.

In addition, it is found that there is not a significant change in computational complexity for the EVRP with uncertain arrival/departure times described by a RO-approach, compared to the deterministic EVRP discussed in Chap. 3.

Chapter 5

Stochastic Sequential Decision Problem

In Chap. 4, we discussed how the operations of electric towing trucks can be optimized under uncertain arrival and departure times, using a Robust Optimization (RO)-approach. In this approach, the schedule is determined at the beginning of the day. A large disadvantage of this approach is that information about the actual arrival/departure times of aircraft that becomes available throughout the day is not taken into account. In the RO-approach of Chap. 4, trucks were not scheduled to go to another aircraft or to return to the depot until the latest sampled arrival time. However, this waiting is not necessary if we take into account information about the known arrival/departure times throughout the day. In this chapter, we discuss how the operations of electric towing trucks under uncertain arrival/departure times of aircraft can be optimized by a dynamic approach.

In Sec. 5.1, we discuss what dynamic programming is and how to determine the optimal operations under uncertain arrival and departure times in a dynamic way. In Sec. 5.2, we discuss how approximations can help with the problem of the curse of dimensionality for dynamic programs. Before we discuss in Sec. 5.4 how we determine the optimal policy, we discuss the six elements of a Stochastic Sequential Decision Problem (SSDP) which formulates the problem of an Electric Vehicle Routing Problem (EVRP) with uncertain arrival/departure times of aircraft, described by a dynamic approach. This is followed by the model formulation and the introduction of the developed algorithm to find the optimal policy in Sec. 5.4. In Sec. 5.5, we discuss how the presented dynamic model is implemented in code. This is followed by the results of this model in Sec. 5.6, where we focus on the comparison of the deterministic, RO-based, and the dynamic model.

5.1 Dynamic Programming

In Chap. 4 we considered that the actual arrival/departure times of aircraft are uncertain until the moment in time, the aircraft actually arrives or departs. However, in reality, as soon as an aircraft takes off, it is usually known when it will land. So prior to the actual arrival of an aircraft, it is known when it will land. The departing time of an aircraft depends, among other things, on the success and possible delay of the ground operations during the turn-around. So a specific moment in time cannot be pointed out at which it is certain what the departure time of a departing aircraft is. However, it can be stated that it is known prior to the actual departure time when the aircraft will depart. For this thesis, we make the assumption that 2 hours prior to the scheduled arrival/departure time, we know what the actual arrival/departure time will be.

As the information about the actual arrival/departure times of aircraft becomes available throughout the day, one would like to adjust the schedule of the electric towing trucks according to this information. This way, trucks do not have to wait until the latest sampled realization of an arrival/departure time, as was the case for the RO-based model. As the delays are considered normally distributed N(-2.73, 13.75) for arriving aircraft and N(-1.54, 10.49) for departing aircraft, this waiting time may be long. Adjusting the schedule of the electric towing trucks throughout the day by the information that becomes available, requires a *dynamic model*.

In the field of dynamic programming, decision problems are broken down into smaller sub-problems, where a sequence of decisions is made over time. The decisions made at earlier moments in time may influence the options of decisions that can be made later in time. A dynamic program seeks to make the decisions over time that minimizes (or maximizes) the objective function. The *value function* is the function that denotes the minimum (maximum) value of the objective function at every state in time subject to the constraints. The value functions of dynamic programs are usually expressed as,

$$V_t(S_t) = \min_{a_t} \big(C_t(S_t, a_t) + \gamma\, \mathbb{E}(V_{t+1}(S_{t+1}|S_t)) \big), \tag{5.1}$$

where V_t represents the value function at time t and S_t represents the state at time t, $C_t(S_t, a_t)$ the direct costs at time t of being in state S_t and action a_t is chosen, and γ is the discount factor. Important is that the values at earlier moments in time can be determined recursively by the *Bellman equation*. However, in case the transition function is unclear, for example, unknown exogenous information becomes known over time, one cannot determine the transition from state to state. In addition, we will have to deal with the *curse of dimensionality*. Eq. 5.1 requires looping over all states to determine the expected value of the value function. The state-space can be large and becomes even larger when including the uncertainty of arrival/departure times. We explain more about the *state variable* in Sec. 5.3.2, but to motivate that the state-space becomes very large, let us for now consider an EVRP of 50 flights and 13 trucks, like we presented in earlier chapters. In order to give an idea of the size of the state-space, we make the assumption that we discretize time, the battery load, and discretize and bound the delay of aircraft. If we discretize the time of a day into segments of a minute (1440 segments), and we discretize the battery load of trucks in segments of 0.5 kWh (300 segments), and we discretize and bound the possible delay of aircraft in 40 segments, the state-space of an EVRP of 50 flights and 13 trucks consists of: $(50 \times 1440 \times 300)^{13} \times (2 \times 40)^{50} \approx 3 \cdot 10^{190}$ states. Computational it is not desirable to loop over all states at every decision epoch. The next section explains how to prevent looping over all states at each decision epoch.

5.2 Stochastic Sequential Decision Problems

In a Stochastic Sequential Decision Problem (SSDP), decisions are made sequentially under some uncertainty. An example of this is Approximate Dynamic Programming (ADP), whereby *stepping forward in time* and *approximating* the value function, results in not having to loop over the whole state-space at each decision epoch to determine the value function. A well-known method for ADP is the *Approximated Value Iteration* algorithm, where an approximate value function is learned, hoping that the final approximate value function results in a good *policy*. In this section, we present a similar method, a Stochastic Sequential Decision Model (SSDM), that does not require learning an approximate value function, like is done for an ADP.

Before we present this model in detail, we must have made a clear distinction between a SSDP and a SSDM. This is needed, as in the excellent overview paper, *"Clearing the Jungle of Stochastic Optimization"* [62], Powell discusses that (for example) a dynamic programming model and an approximate dynamic programming model are not a model, but instead they are *classes of policies* for solving dynamic programs. So this leads us to our definitions of a SSDP and a SSDM.

Definition 5.2.1 (Stochastic Sequential Decision Problem (SSDP))**.** A SSDP is a problem where decisions need to be made sequentially under uncertainty. A SSDP consists of a defined state-space, action-space, exogenous information distribution, transition functions, and an objective function.

Definition 5.2.2 (Stochastic Sequential Decision Model (SSDM))**.** A SSDM is a model that consists of a SSDP and a description of how the optimal policy is sought.

5.3 The Five (Six) Elements of our SSDP

According to Powell, there are five elements of a SSDP. In this section, we discuss each element specifically and describe what these elements represent for an EVRP where the arrival/departure times of aircraft are uncertain. This section is followed by Sec. 5.4, where we discuss how to find an optimal policy and thus what a SSDM of an EVRP with uncertain arrival and departure time is.

According to Powell, a SSDM can be described by five elements. Most SSDPs can be described by these five elements. However, I would argue that an element needs to be added for an EVRP described by a SSDM, namely the *decision epoch*. So the six elements of an EVRP described as a SSDM are:

1. Decision epoch
2. State
3. Actions
4. Exogenous information
5. Transition function
6. Objective function

5.3.1 Decision Epoch

A decision epoch, T_p, is a moment in time decisions are made. Here, T_p is the p^{th} moment in time decisions are made. Especially for an EVRP it is essential to discuss what the decision epochs are. There are two "types" of moments in time that require decision-making. Namely, (1) when a truck is done with a tow a decision needs to be made regarding what it should do next. In addition, (2) decisions need to be made for charging trucks.

However, it is not trivial what moment in time decisions need to be made for charging trucks: when do we reconsider whether a truck needs to remain to charge, adapt the charging speed or stop charging? Here we choose to reconsider what charging trucks must do when exogenous information becomes available. This is because, when exogenous information becomes available, trucks (may) need to adapt what they are doing, but trucks that are towing when exogenous information becomes available, are not allowed to change tasks while performing a tow. So decisions can only be made for trucks at the depot at these decision epochs. For this thesis, it was assumed that exogenous information becomes available 2 hours prior to the scheduled arrival/departure time of each aircraft. So in conclusion, we choose the set of decision epochs to consist of all moments in time some trucks are done with a tow and all moments in time exogenous information becomes available.

5.3.2 State description

Powell discusses that a definition of a state variable is not that trivial and that in different study books different definitions of a state variable are given. We will follow the definition of the *state variable* that Powell gives in [62],

Definition 5.3.1 (State variable)**.** A state variable is the minimally dimensioned function of history that is necessary and sufficient to compute the *action function*, the *transition function*, and the *contribution function*.

This definition states that the *state*, S_p, at time T_p includes the minimal amount of information needed to determine the actions that can be taken, the transition to the next state for every action chosen and the objective value function. This minimum amount of information of an EVRP with uncertain arrival and departing times of aircraft, at the p^{th} decision epoch T_p, consists of,

- The assigned request or assignment to the depot of every truck: $l_k \in I \cup D, k \in K$, where I is the set of requests, D the set of depots and K the set of trucks.
- The moment in time at which each truck is done with the tow or the earliest moment in time exogenous information becomes available for trucks that are at the depot: $t_k \in [0, \infty), k \in K$.
- The battery level of each truck: $q_k \in [0, \mathcal{C}_c), k \in K$
- The status of each request (handled, scheduled to be handled, or not scheduled to be handled yet): $h_i \in \{0, 1\}, i \in I$. Here, $h_i = 1$ when request i is handled or scheduled to be handled at T_p, and $h_i = 0$ if there is not yet a truck assigned to request i.
- All exogenous information currently available about the delays of each request: $\mathcal{W}_p$. $\mathcal{W}_p$ consists of all information gathered about the delays of each request throughout time, $W_1, W_2, \cdots, W_p$. Here, W_p takes the form of $W_p \in \{\{?\} \cup (-\infty, \infty)\}^{|I|}$, where W_{p_i} is the exogenous information of the delay of request i that becomes available between time T_{p-1} and T_p about request i. If $W_{p_i} = \{?\}$, no exogenous information became available about request i between T_{p-1} and T_p. It is assumed that per request information is obtained once, such that $\mathcal{W}_p$ is the vector that contains all information about all requests gathered until T_p and is of the form $\mathcal{W}_p \in \{\{?\} \cup (-\infty, \infty)\}^{|I|}$. For example in the case of 5 requests, consider that at decision epoch p it is only known that the aircraft of request 4 will be 2 minutes early, $\mathcal{W}_p = \{?, ?, ?, -2, ?\}$. If we then obtain the exogenous information between decision epoch p and $p+1$ that the aircraft of request 5 will be 4 minutes late, $W_{p+1} = \{?, ?, ?, ?, 4\}$, then $\mathcal{W}_{p+1} = \{?, ?, ?, -2, 4\}$. As we do not require the information about when the exogenous information became available to compute the action function, transition function, and the contribution function, this does not need to be included. This is why we include $\mathcal{W}$ in the state and not W.
- Total charging costs: $C \in [0, \infty)$.

According to Powell, a state must be the minimal amount of information to determine (1) the actions that can be taken, (2) transition to the next state, and (3) the objective value function. From the list of information, just stated, we can determine what actions can be taken at T_p, as we know for which trucks a decision needs to be made, as we know when every truck is done with its current job (so we know which trucks are finished) and we know which trucks are at the depot. From the status of each request and the exogenous information, one can determine the set of possible actions for the set of trucks that a decision needs to be made, so the first requirement of a state variable is met. A transition from the current state to the next state can be computed by updating the state by the action made and the exogenous information. Lastly, the objective value function can be determined for all T_p as the state includes the total electricity costs at T_p and the associated costs of each action can be added.

If we denote $(l,t,q) = (l_k, t_k, q_k)_{k\in K}$ and $(h) = (h_i)_{i\in I}$ then the state at the p^{th} decision epoch, T_p, of an EVRP under uncertain arrival and departure times of aircraft, described as a SSDP, is,

$$S_p = ((l,t,q),(h),\mathcal{W}_p,C) \tag{5.2}$$

So the total state-space is,

$$S = I^{|K|} \times [0,\infty)^{|K|} \times [0,\mathcal{C}_c)^{|K|} \times \{0,1\}^{|I|} \times \{\{?\}\cup(-\infty,\infty)\}^{|I|} \times [0,\infty) \tag{5.3}$$

The initial state at $T_0 = 0$, where all trucks are at the depot, nothing is known about the arrival and departure delays, no trucks are assigned and the total electricity costs are zero, is,

$$S_0 = ((0,0,\mathcal{C}_c)^{|K|},(0)^{|I|},\{?\}^{|I|},0) \tag{5.4}$$

If one of the *absorbing states* is visited, the decision-making process is stopped. The set of absorbing states is,

$$S_P = \{((0,t,q)^{|K|},\ (1)^{|I|},\ \mathcal{W}_P,\ C) : t\in[0,\infty),\ q\in[0,\mathcal{C}_c),\ \mathcal{W}_P\in(-\infty,\infty)^{|I|},\ C\in[0,\infty)\} \tag{5.5}$$

Here, T_P represents the final decision epoch.

5.3.3 Actions

The third element of a SSDP, is the action, a. At each decision epoch, p, an action, a_p, needs to be chosen. In Sec. 5.4, we describe how we seek the optimal policy and thus how actions are chosen. For now, we assume we know how actions are chosen. But this requires a set of actions that can be chosen from at each decision epoch. So how do we define this set of actions when in the state S_p?

For this we introduce, $\mathcal{K}_p$, which is the set of trucks for which a decision needs to be made in decision epoch p, $\mathcal{K}_p = \arg\min_{k\in K} t_k(p)$. All trucks $k \in \{K \setminus \mathcal{K}_p\}$ are assigned, so no decision needs to be made for these trucks. We consider action a as a $|K|$-dimensional vector where the k^{th} element is the action of truck k, directing truck k to a location $l_k \in I \cup D$. In Sec. 5.4, we discuss the algorithm to find the optimal policy. It will be shown that we loop over all actions in the action-space at each decision epoch. So it is important to minimize the size of the action-space at each decision epoch for computational reasons. However, defining an action-space that is too small may result in not finding the optimal solution as some actions are excluded. Fig. 5.1 schematically depicts the possible actions that can be chosen for trucks, for which a decision needs to be made at T_p, when at a certain location, as described by Eq. 5.8-Eq. 5.10. We define the set of actions that can be chosen in state S_p as,

$$\mathcal{A}_p = \{a \in \{I\cup D\}^k :$$

$$a_k = l_k, \qquad \forall k \in \{K\setminus\mathcal{K}_p\}, \tag{5.6}$$

$$a_k \neq a_j, \qquad \forall k,j\in K : k\neq j, a_k, a_j \notin \{d_{1_{c_0}}, d_{1_{c_1}}, d_{1_{c_2}}, d_{2_{c_0}}, d_{2_{c_1}}, d_{2_{c_2}}\}, \tag{5.7}$$

$$a_k \in \{j : h_j = 0, \forall j\in I,\ d_{1_{c_0}}, d_{1_{c_1}}, d_{1_{c_2}}\}, \qquad \forall k\in\mathcal{K}_p : l_k \notin \{d_{1_{c_0}}, d_{1_{c_1}}, d_{1_{c_2}}, d_{2_{c_0}}, d_{2_{c_1}}, d_{2_{c_2}}\}, \tag{5.8}$$

$$a_k \in \{l_k,\ d_{2_{c_0}}, d_{2_{c_1}}, d_{2_{c_2}}\}, \qquad \forall k\in\mathcal{K}_p : l_k \in \{d_{1_{c_0}}, d_{1_{c_1}}, d_{1_{c_2}}\}, \tag{5.9}$$

$$a_k \in \{j : h_j = 0, \forall j\in I,\ l_k\}, \qquad \forall k\in\mathcal{K}_p : l_k \in \{d_{2_{c_0}},\ d_{2_{c_1}},\ d_{2_{c_2}}\}\}, \tag{5.10}$$

where we denote $d_{r_{c_g}}$ as the action/location that a truck goes to the r^{th} depot to charge with the charging speed of option g. So $d_{1_{c_0}}$ is the action of a truck going to the first depot to charge with the charging speed of option 0. In the formulation of the set of actions that can be chosen from, in state S_p, Eq. 5.6 and Eq. 5.7

are regarding general "rules". For example, in Eq. 5.6 we ensure only a decision is made for the trucks that a decision needs to be made for. Eq. 5.8-Eq. 5.10 are regarding the actions that can be chosen for trucks that are at a specific location.

Eq. 5.7 ensures that 2 trucks may not be assigned to the same request. Eq. 5.8 allows trucks for which a decision needs to be made, that are currently finished with a tow (so not at the depot), to be assigned either to a request that has not yet been assigned or to go to the first depot to charge with the charging speed of either option 0, 1, or 2. Eq. 5.9 forces trucks that are currently at the first depot, to either remain there and to charge with the same charging speed the truck is currently charging with, or to go to the second depot to charge with a certain charging speed. Eq. 5.10 forces trucks for which a decision needs to be made, that are present at the second depot, to remain there charging with the charging speed the truck is currently charging with, or to go to a request that has not yet been assigned.

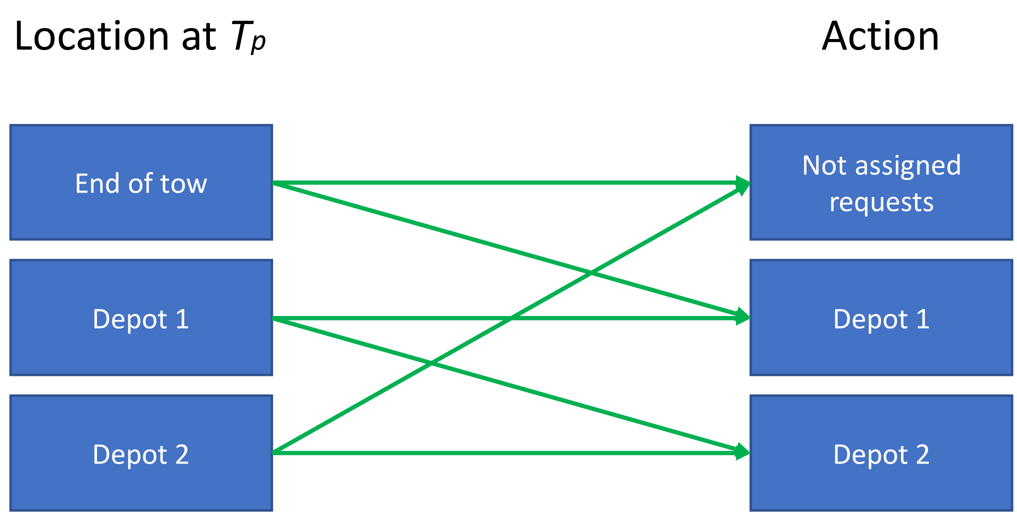


Figure 5.1: Schematic representation of the possible actions trucks have, for which a decision needs to be made at T_p, when at a certain location, as described by Eq. 5.8-Eq. 5.10. The green arrows indicate where a truck may go when at a specific location.

5.3.4 Exogenous information

The fourth element of a SSDP, is exogenous information. As explained in Sec. 5.3.2, the exogenous information is observed as a sequence $W_1, W_2, \cdots, W_p$, where the index is the decision epoch and W_p represents the exogenous information that becomes available between W_{p-1} and W_p. As we assume information about each request becomes available once, all known information about all requests can be expressed in $\mathcal{W}_p \in \{\{?\} \cup (-\infty, \infty)\}^{|I|}$. So the states, actions, and information evolve as follows,

$$(S_0, a_0, W_1, S_1, a_1, W_2, \cdots, S_p, a_p, W_{p+1}, \cdots, S_P),$$

where S_P is an absorbing state. We consider the exogenous information, W, which is the actual delay of aircraft, to arrive for each request 2 hours before the scheduled arrival/departure time and this delay of the arrivals/departures is normally distributed as described in Sec. 4.1.

5.3.5 Transition function

The fifth element of a SSDP is the transition function. In Sec. 5.4 we will discuss how actions are chosen and how we seek the optimal policy. But once an action is chosen, a transition to the next state needs to be formulated. This is done by a *transition function*. For now, we assume we made a decision a_p while being in state $S_p = ((l_p, t_p, q_p), (h_p), \mathcal{W}_p, C_p)$. All elements of S_p can be updated deterministically, except for $\mathcal{W}_p$. We split the transition from S_p to S_{p+1} into 2 steps, namely the transition from S_p to S_p^a, where a is the chosen action and from S_p^a to S_{p+1}. Here, S_p^a is the state after we chose action a, but before the exogenous information at decision epoch T_{p+1} arrived, such that $S_p^a = ((l_p^a, t_p^a, q_p^a), (h_p^a), \mathcal{W}_p^a, C_p^a)$ is the *post-decision state*. S_{p+1} is the *pre-decision state*. So the states, actions, pre-decision states, exogenous information, and the post-decision states evolve as,

$$(S_0, a_0, S_0^a, W_1, S_1, a_1, S_1^a, W_2, \cdots, S_p, a_p, S_p^a, W_{p+1}, \cdots, S_P).$$

Post-decision state

The transition from S_p to the post-decision state S_p^a is done by updating l_p, t_p, q_p, h_p and C_p. Here, we do not update $\mathcal{W}_p$. Updating to the post-decision state is done in the following way, where we leave the index p out, for simplicity,

$$l_k^a = a_k, \quad \forall k \in K \tag{5.11}$$

$$t_k^a = \begin{cases} t_k + t(l_k, l_k^a), & \forall k \in \mathcal{K}_p \\ t_k, & \forall k \in \{K \setminus \mathcal{K}_p\} \end{cases} \tag{5.12}$$

$$q_k^a = \begin{cases} q_k + q(l_k, l_k^a), & \forall k \in \mathcal{K}_p \\ q_k, & \forall k \in \{K \setminus \mathcal{K}_p\} \end{cases} \tag{5.13}$$

$$h_i^a = \begin{cases} 1, & \forall k \in \mathcal{K}_p : l_k^a = i, i \in I \\ h_i, & \text{otherwise} \end{cases} \tag{5.14}$$

$$C^a = C + \sum_{k \in K} C(a_k). \tag{5.15}$$

Eq. 5.11 describes how l_k^a is updated, by the chosen action. As the action vector consists of the updated assigned requests of trucks or the allocation of a truck to the depot, this action vector represents the updated vector l_k^a. Eq. 5.12 describes how the time vector, which describes at what moment in time a truck is done with a tow or when new exogenous information arrives for charging trucks, is updated. For every truck that a decision is made for, the time is updated by adding $t(l_k, l_k^a)$. This value is the time needed to perform the tow or the time it takes to drive without towing an aircraft. And for trucks that are assigned to go to the depot, $t(l_k, l_k^a)$ must be the next moment in time exogenous information becomes available. Eq. 5.13 represents the updating of q_k^a. This vector represents the battery level of each truck. This is updated by adding $q(l_k, l_k^a)$ for trucks that a decision is made for. For trucks at the depot, $q(l_k, l_k^a)$ is positive and depends on the time between 2 decision epochs and the charging speed. For trucks that are assigned to tow an aircraft (or to drive while not towing), $q(l_k, l_k^a)$ is negative and this value corresponds to the electricity needed to tow the aircraft (drive empty). Eq. 5.14 represents the updating of the vector that keeps track of the assigned requests. For trucks that a decision is made for, where their updated assigned request is not to go to the depot (so to go to another request), the element corresponding to the request of h_i^a is updated to 1. All other elements remain the same as before the decision is made. Lastly, Eq. 5.15 shows how the total electricity costs are updated. Here, $C(a_k)$ corresponds to the direct electricity costs associated with actions a_k, $\forall k$ which are the actions chosen for all trucks. The costs associated with all actions chosen depend on the time between 2 decision epochs and the charging speed, trucks at the depot charge with.

Pre-decision state

From the post-decision state S_p^a, a transition function to the pre-decision state S_{p+1} must be defined. This transition updates the state by including the exogenous information that becomes available between 2 decision epochs, W_{p+1}. Remember that $\mathcal{W}_p$ is defined as all exogenous information about every request obtained until decision epoch p, while W_{p+1} is the information that becomes available between decision epochs p and $p+1$. The transition to the pre-decision state goes in the following way,

$$\mathcal{W}_{p+1,i} = \begin{cases} W_{p+1,i}, & \forall i \in I : W_{p+1,i} \notin \{?\} \\ \mathcal{W}_{p,i}, & \forall i \in I : W_{p+1,i} \in \{?\} \end{cases} \tag{5.16}$$

Eq. 5.16 describes that $\mathcal{W}_{p+1}$ is the vector containing all information available at decision epoch $p+1$. This consists of all information that was already known, $\mathcal{W}_p$ and the information, W_{p+1}, that became available between decision epoch p and $p+1$.

5.3.6 Objective function

The objective function is the sixth element of a SSDP. As the arrival and departure times are uncertain, the objective of the EVRP with uncertain arrival and departure times, described by a dynamic model, is to minimize expected electricity costs. So the objective is,

$$\min_{\pi \in \Pi} \mathbb{E}^{\pi} \sum_{p=0}^{P} C(S_p, a_p^{\pi}(S_p)), \tag{5.17}$$

where π is a policy of the set of possible policies Π. The optimal stationary policy is denoted as π^*. This policy will result in minimal expected electricity costs. Here, $C(S_p, a_p^{\pi}(S_p))$ represents the direct electricity costs in state S_p, when action $a_p^{\pi}(S_p)$ is chosen according to the policy π.

All six elements of a SSDP that describe an EVRP with uncertain arrival and departure times are introduced. Fig. 5.2 schematically shows an overview of the timeline of an EVRP described by a SSDP.

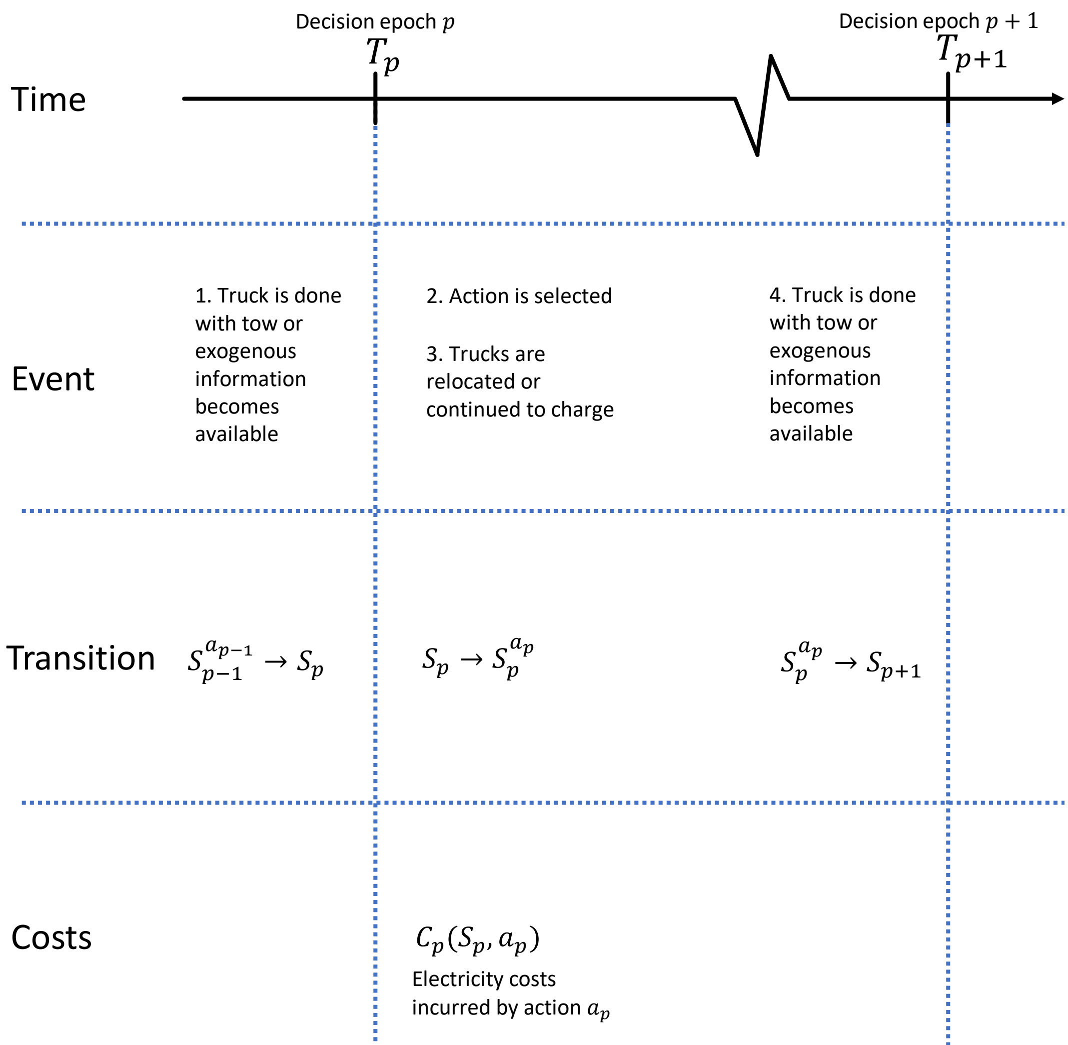


Figure 5.2: Schematic representation of the timeline of an EVRP with uncertain arrival and departure times of aircraft, described as a SSDP, adapted from [63].

5.4 Finding the Optimal Policy on a SSDP

We seek to find the optimal *policy*, that minimizes the expected total electricity costs. So, we seek to find the optimal (stationary) policy, π^* that produces actions $a_p \in \mathcal{A}_p$, where $\mathcal{A}_p$ is the set of feasible actions that depend on the state S_p, that results in the minimal expected total electricity costs. The main question is how will we find this optimal policy. By the elements of the SSDP introduced in the previous section, we know a few things about our EVRP. Namely, we know (1) the state-space is very large, as shown in Sec. 5.1. However, (2) the action-space at every decision epoch is not necessarily large, as the set $\mathcal{K}_p$ is at most the whole fleet, but by the way we defined a decision epoch, $\mathcal{K}_p$ will consist of a single (or a few) trucks at most decision epochs. Looking at the options of actions of each of these trucks, we see that there are only a few possibilities per truck, resulting in a relatively small set of possible actions at each decision epoch. And (3) the EVRP still has the constraints that all aircraft of the sampled arrival/departure times need to be towed on time. Lastly, (4) it is very difficult to determine a transition function from state to state. These 4 important characteristics of the EVRP can help us determine a way to find an optimal policy.

Due to the large state-space and the fact that it is difficult to determine a transition function between states, one would prefer an algorithm that does not include looping over all states or one that requires a transition function. On the other hand, looping over the action-space would not be a problem. We present a Dynamic Approximated Cost Algorithm (DACA) that takes advantage of these points. This DACA ensures all constraints regarding time-windows and battery level of trucks, as presented for the deterministic and RO-based model, to be satisfied for all sample paths. The DACA determines at every decision epoch what action needs to be chosen, by considering what action results in the lowest electricity costs at the end of the day for all sample paths.

Algorithm 1: Dynamic Approximated Cost Algorithm (DACA)

1. Sample Sample n random sample-paths of the joint delay distribution, $\hat{\Omega}^n \in \Omega$.
2. Initialize Set an initial state S_0, set $p = 0$.
3. Update Determine the set of trucks for which a decision needs to be made, $\mathcal{K}_p$.
4. Update Determine set of actions, $\mathcal{A}_p$ that can be taken at epoch p.
5. Iteration For $\forall\ a_p \in \mathcal{A}_p$, $\forall n$:

Determine the total electricity costs, considering being in state S_p and a_p is the chosen action and $\hat{\Omega}^n$ is the realization of the flight schedule:

$$V(S_p^{a_p}, \hat{\Omega}^n) = \min\ \text{MILP}(S_p^{a_p}, \hat{\Omega}^n) \tag{5.18}$$

6. Decision-making

$$\tilde{a}_p = \underset{a_p \in \mathcal{A}_p}{\operatorname{argmin}} \sum_{\hat{\Omega}^n \in \Omega} V(S_p^{a_p}, \hat{\Omega}^n) \tag{5.19}$$

7. Update and increment Update state, $S_p^{\tilde{a}_p} \to S_{p+1}$.
8. Increment or stop If $S_{p+1} \in S_P$: stop, otherwise: $p = p + 1$ and go to step 3.

Algorithm 1 samples in the first step n sample-paths of the flight schedule, where n is preferably a large number. So n samples are drawn from the joint distribution of all scheduled arrivals/departures and the probability delay functions. In step 2, the state is initialized as $S_0 = ((0,0,\mathcal{C}_c)^{|K|}, (0)^{|I|}, \{?\}^{|I|}, 0)$. In step 3, the set of trucks for which a decision needs to be made is determined. Then this is followed by determining the set of possible actions, $\mathcal{A}_p$, in step 4. This is done as explained in Sec. 5.3.3. Step 5 is the step where for every possible action and for every sampled sample path, the electricity costs at the end of the day is determined, by solving the deterministic model, MILP, of Chap. 3, where it is considered being in state S_p, action a_p is chosen and $\hat{\Omega}^n$ is the deterministic flight schedule. So this step requires $|\mathcal{A}_p| \times n$ times solving a deterministic EVRP at every decision epoch. This is indicated in the algorithm by Eq. 5.18. We denote $V(S_p^{a_p}, \hat{\Omega}^n)$ as the electricity costs at the end of the day when in state S_p and an action a_p is chosen and $\hat{\Omega}^n$ is the sample path. Note that, if for example at T_p the actual arrival time of request i is known, then $\hat{\Omega}^n$ does not include sampled realizations of the arrival/departure time of request i, now $\hat{\Omega}^n$ will contain the actual arrival/departure time for all sample-paths. If an action a_p results in an infeasible model, $V(S_p^{a_p}, \hat{\Omega}^n) = \infty$.

In step 6, the actual decision-making is done, by determining which action from the set $\mathcal{A}_p$ results in the lowest expected electricity costs at the end of the day by summing over the electricity costs determined for every sampled flight schedule. This is indicated in the algorithm by Eq. 5.19. In step 7, the state is updated according to the chosen action $\tilde{a}_p$. Lastly, in step 8, if the state is not an absorbing state, the decision epoch is incremented and the procedure continues by going back to step 3. So step 3-7 are repeated until an absorbing state is reached.

The advantages of this algorithm include that this algorithm uses part of the deterministic model. The deterministic model of the EVRP is tested and analyzed in Chap. 3. In addition, the only approximation that is done is that the action is chosen by sampling n scenarios of the delays of flight schedules, instead of using approximating that might lead to exploitation, like for an ADP. In addition, one is not restricted to distributions of the delay. One could also use historical data by using scenario sampling, where for example dependencies between delays may be included. This would be more difficult when being restricted to use distributions.

5.5 SSDM with a DACA Code Implementation

Several implementation details need to be mentioned for completeness. The implementation of steps 1-4 of the DACA presented in Algorithm 1 is straightforward, however, for step 5 we use part of the code of the deterministic model as presented in Chap. 3. In step 5 of Algorithm 1, we loop over all actions $a_p \in \mathcal{A}_p$ and we loop over all n sample-paths $\hat{\Omega}^n \in \Omega$. This way, we determine for every combination of $a_p \in \mathcal{A}_p$ and $\hat{\Omega}^n \in \Omega$, the total electricity costs, $V(S_p^{a_p}, \hat{\Omega}^n)$, of being in state $S_p^{a_p}$, assuming full knowledge of the remainder of the flight schedule $\hat{\Omega}^n$.

The state S_p can be considered as the initial state where some DVs are fixed. We use this for the implementation of the DACA. $S_p^{a_p}$ is determined for every $a_p \in \mathcal{A}_p$, by constraining the DVs associated with actions $a_0, a_1, \cdots, a_{p-1}$ to "create" state S_p and by iterating over the actions $a_p \in \mathcal{A}_p$, we fix the DVs associated with the different $a_p \in \mathcal{A}_p$, to "create" $S_p^{a_p}$. By determining $V(S_p^{a_p}, \hat{\Omega}^n)$, we consider the sample-path $\hat{\Omega}^n$ to be the deterministic flight schedule and we solve the deterministic EVRP. Then in step 6, a decision is made, regarding what action should be chosen, by determining which action results in the lowest total electricity costs for all sample-paths.

For this implementation of the DACA of an EVRP using the deterministic model of Chap. 3, it is important to note that this fixing of the DVs is not straightforward. For example, one must, in addition to the DVs $x_{i,j,k}$ associated with the chosen action $\tilde{a}_p$, fix the time charged at the depot at each decision epoch. For example, if truck k, after towing the aircraft of request i, was assigned to go to the depot to charge with charging speed c at decision epoch p, and at decision epoch $p+1$ it is assigned to remain charging, this must be included in the "fixed DVs" of state S_{p+1}. This is done by adding the constraint,

$$t_{i_c} \geq T_{p+1} - T_p + t_{i,d_c,k}. \tag{5.20}$$

This constraint states that the charging time of the truck that towed the aircraft of request i, must be equal or larger to the time between the decision epoch $p+1$ and the decision epoch p, plus the time it takes to get to the depot after towing the aircraft. Then if it is decided in decision epoch $t+2$, truck k must still remain charging, the constraint is updated to,

$$t_{i_c} \geq T_{p+2} - T_p + t_{i,d_c,k}. \tag{5.21}$$

Similar constraints are implemented for trucks that adapt the charging speed at a certain decision epoch.

Another point of implementation that should be addressed is that for the initial state, S_0, we set a random truck to tow the aircraft that needs to be towed earliest in time. This is done as this will not affect the total electricity costs, but at the first decision epoch, the set of actions that can be chosen from is large, as a decision needs to be made for all trucks, as all are at the depot. If we initialize a random truck to serve the first aircraft that needs to be towed, this reduces the set of actions that can be chosen from in the first decision epoch significantly, without affecting the solution. If we do not implement this, the computation time of the first decision epoch (for a flight schedule of 12 flights and a electric towing truck fleet of 4 trucks) will be longer than a day.

Another point of implementation that should be addressed that may influence the operations of the trucks that we used is the following. When we determine the set of possible actions, we limit trucks to only be assigned to one of the three earliest requests at that moment in time. When allowing all future requests, the set of actions that can be chosen from increases significantly, while it is most likely that a truck will be assigned to a request that needs to be towed within the near future, otherwise a truck is most likely to be assigned to go to the depot. However, it is important to keep in mind that the implementation may influence the solution, as the set of actions that can be chosen from might be too small. If this happens, we expect the expected total costs to increase significantly at a certain decision epoch.

One last important implementation detail is that we stop with the decision-making of the DACA after the arrival/departure times of all requests are known, as a deterministic model remains. So we do not continue decision-making by the DACA until the absorbing state is reached. However, the end state of the best-found solution of this deterministic model is an absorbing state.

5.6 Results

In this section, the results of the EVRP with uncertain arrival and departure times of aircraft at an airport, described as a SSDM will be presented and discussed. Before we present and discuss the results, we must clarify two more points regarding the results: (1) the number of sample-paths drawn from the joint delay distribution, and (2) the size of the problem in terms of the number of aircraft and trucks.

The first point that needs clarification is the number of samples drawn from the joint delay distribution. For the RO-based model we chose the number of samples drawn such that the probability that an aircraft actually arrives before a truck is present at the start location, is considered low enough. However, it is difficult to say what the probability is that no truck can be assigned to tow an aircraft on time for the SSDM. This is due to the fact that an early arrival of a certain aircraft may result in a lower objective value but it may also result in a very high objective value or even in an infeasible model. In addition, for the SSDM we do not know when a truck will be scheduled to be at the start location of a request. We only know it determines what actions to choose in every decision epoch by determining which action results in the lowest objective value function for many scenarios.

So we cannot base the number of samples drawn on the probability that a truck is on time. However, we do know that when the number of samples drawn is higher, the probability that a truck is tardy, decreases. In addition, it is found that the computation time of this model is very long, so as a trade-off between the probability that a truck is on time and the computation time, we have decided to sample 50 sample paths.

The second point that needs clarification is the size of the problem we will consider. Although we defined a small action-space at each decision epoch, as explained in Sec. 5.3.3, the computation time is still very long, even for a small fleet of trucks and a small number of aircraft. For example, if we set the maximum solving time to solve the deterministic problem (Eq. 5.18) of an EVRP of 12 flights and 4 trucks, to 5 seconds and we sample 50 flight schedules, determining the operations of that day already takes about 6 hours. In this section, we present the results of the best-found truck schedule of a fleet of 4 trucks, that tow 12 aircraft. This is the minimal found amount of trucks needed to serve all aircraft determined by the SSDM. We will compare the best-found truck schedule found by the DACA with the results obtained by the deterministic and RO-based model.

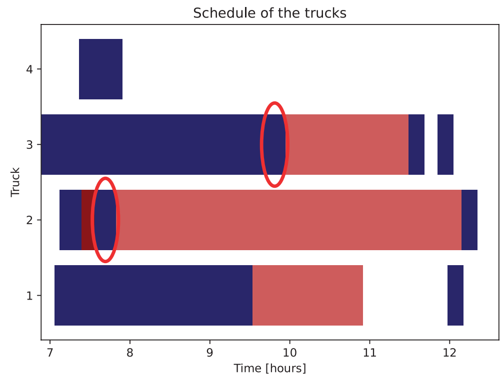
	SSDM	Deterministic model	RO-based model
Number of flights	12	12	12
Number of trucks	4	4	5
Battery capacity [kWh]	150	150	150
Service time [min]	5	5	5
Number of samples	50	N/A	300

Table 5.1: Overview of the problem parameters of the different models that are compared in this chapter.

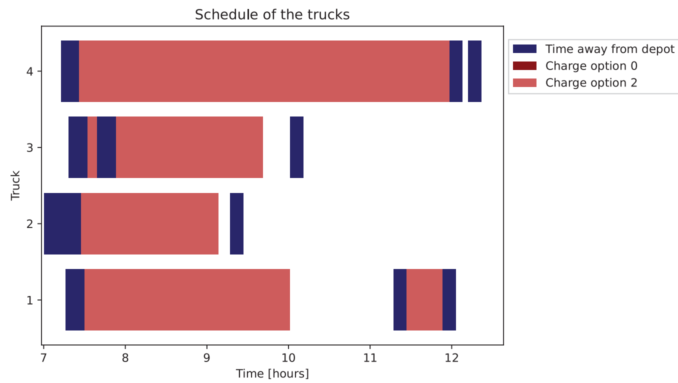
Fig. 5.3a shows a best-found truck schedule of a homogenous fleet of 4 trucks that tow 12 aircraft under uncertain arrival/departure times, determined by the DACA. The actual flight schedule is determined by sampling a flight schedule. An overview of the parameters used for every model presented in this chapter is given in Tab.5.1. The electricity costs due to charging during the day of this truck schedule are € 17.75. The total electricity costs including the costs associated with the charging of the trucks, such that they are fully charged at the beginning of the day, are € 843.35. In Appendix. F, we show and discuss the best-found truck schedule of four other runs, where 50 other scenario flight schedules were sampled and a different actual flight schedule was sampled. All four runs resulted in a found truck schedule that is able to tow all aircraft on time. Due to the long computational time, the number of runs performed is limited. So from these results, no hard conclusions can be drawn, as only five runs were performed.

The blue dots in Fig. 5.4 show the objective values determined by Eq. 5.18 at each decision epoch, for every action and every sample-path. For aesthetic reasons, the objective values of models of a combination of an action a_p and a sample-path $\hat{\Omega}^n$ that results in an infeasible model, $V(S_p^{a_p}, \hat{\Omega}^n) = \infty$, is indicated by a blue dot with a value of 3 times the value of the maximum objective value found for a feasible model. So these are the dots at the top of the graph. The red line indicates the expected total costs at the end of the day for the action that is chosen in that decision epoch. The blue dots below the red line correspond to actions that for some sample paths result in lower electricity costs than the red line at the end of the day, however, these actions do not result in the lowest electricity costs for all sample paths. It can be seen that the expected total cost slightly increases and decreases over the decision epochs, due to exogenous information that becomes available throughout the day. However, no significant steps of the expected objective value are observed at a specific decision epoch. This suggests that the set of actions that can be chosen from at each decision epoch does not exclude actions that would result in a significantly lower expected objective value.

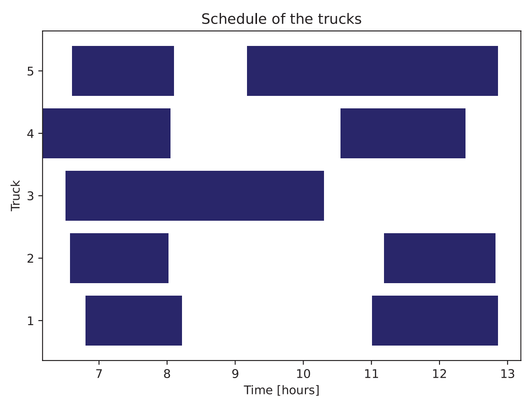
Fig. 5.3b shows the best-found truck schedule of 12 aircraft, with deterministic arrival/departure times, towed by a homogenous fleet of 4 trucks. This schedule is determined by the model presented in Chap. 3. It is important to emphasize that the objective value of the deterministic schedule of the realization of the flight schedule of the SSDM is the lower bound of the objective value of the schedule found by the SSDM. As for the deterministic model all information about the arrival/departure times is known, while for the SSDM this is 2 hours prior to the scheduled arrival/departure and the operations of the trucks may need to be adjusted as a result of the actual arrival/departure times during the day. The total electricity costs of this truck schedule are



(a) SSDM schedule



(b) Deterministic schedule



(c) RO-based schedule

Figure 5.3: Truck schedule for a flight schedule of 12 flights **(a)** Obtained by the uncertain EVRP, described by a SSDM, as described in Chap. 5. The total electricity costs are € 843.35. The bright red ellipses are used for clarification in the main text. **(b)** Obtained by the deterministic EVRP of Chap. 3. The total electricity costs are € 838.09. **(c)** Obtained by the uncertain EVRP, described by a RO-approach of Chap. 4. 5 trucks were needed to tow all aircraft. Trucks were considered to be done with the tow after the maximum sampled arrival time. And the total electricity costs are € 1032. The trucks do not have to charge during the day, as they are considered to be fully charged at the beginning of the day.

€ 838.09. So the electricity costs of the deterministic truck schedule are less, as trucks do not have to charge with a faster-charging speed than the charging speed of option 2, which is needed for the truck schedule determined by the DACA. An overview of these results is depicted in Fig. 5.5.

In more detail, one can see that in the best-found truck schedule determined by the DACA, shown in Fig. 5.3a, that it might have been a better choice to let truck 3 tow the second request that truck 2 tows (indicated by the bright red ellipse around the second tow of truck 2). This way truck 2 did not have to charge with the higher charging speed of option 0. However, at the decision epoch where it was decided that truck 2 towed that request, the arrival time of the second request that truck 3 tows, was not known, as the information about the arrival time of that aircraft became known just before 8 o'clock. This request is also indicated for clarification

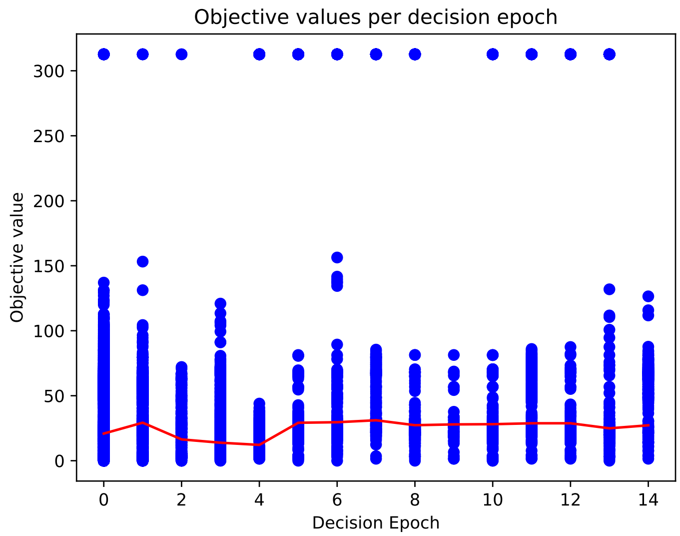


Figure 5.4: The objective values of every combination of the actions that can be chosen at each decision epoch for every sample path, for the truck schedule of Fig. 5.3a. The red line indicates the expected charging costs for the action that is chosen in that decision epoch.

with a bright red ellipse. This has led to the decision that truck 2 charged with a fast charging speed and that it was assigned to tow the request.

Fig. 5.3c shows the best-found truck schedule of a homogenous fleet of 5 trucks, found by a RO-based model, of an uncertain flight schedule of 12 flights, where trucks were considered to wait for an aircraft to arrive/depart until the maximum of the sampled arrival/departure times of each request (option 2) like presented in Chap. 4. 300 arrival/departure times are sampled for each request from the distribution discussed in Sec. 4.1. The electricity costs due to charging during the day of this truck schedule are € 0, as no truck needs to charge during the day. However, the charging costs to charge the trucks to be fully charged at the beginning of the day are € 1032. The trucks are almost all empty at the end of the day. Remember that the trucks charge with the charging speed of option 1 during the might, this is the reason why the electricity costs are significantly high. This model does not minimize for the electricity costs of the charging during the night. The minimum number of trucks needed to tow all aircraft considered by the sampled arrival/departure times on time is 5 trucks.

So the SSDM results in fewer trucks needed to serve all aircraft on time corresponding to the sampled realizations of the flight schedule, compared to the RO-based model. This is due to the fact that for the RO-based model, trucks are occupied longer for each request, as trucks are not scheduled to go to another aircraft or return to the depot until the latest sampled arrival/departure time. An overview of these results is depicted in Fig. 5.5.

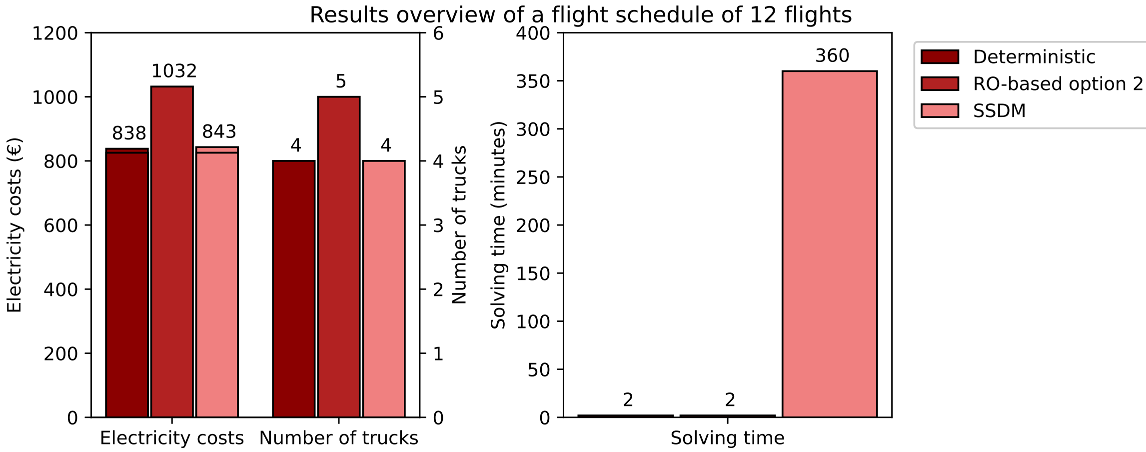


Figure 5.5: Comparison of the results obtained from the deterministic, RO-based model and the SSDM for a flight schedule of 12 flights. The electricity costs due to the charging during the day and due to the charging of the trucks to get them fully charged at the beginning of the day are separated in this graph by a line. The top part of the bar indicates the electricity costs due to the charging during the day.

5.6.1 Main Discussion Points

The main point of discussion of this SSDM solved by the DACA, is the computational time. This model is not suitable to use for large flight schedules (>50 flights), where many trucks are needed. So this model is not directly suitable for usage on a daily basis for an airport. Within the limited time of this research project, there was no time to implement ideas to improve the computation time. However, there are ideas on how to improve this model. Firstly, there might be a more compact way to describe this EVRP, for example, the two-index formulation of Furtado *et al.* [43]. By a more compact formulation, the computation time might reduce. However, as we set a maximum solving time, a compact formulation might only result in a better solution, instead of a reduction of computation time. One could also reduce the solving time by lowering the maximum solving time, however, this is a trade-off as this may lead to a worse solution.

In addition, there are ways to improve the computation time by considering other approximation methods, like the density-based algorithm presented in [64]. Another interesting option would be the Adaptive Variable Neighbourhood Search algorithm, for example, the formulation of Polacek *et al.* [65]. Lastly, there is a whole field of machine learning that can be used to predict the delays in a better way, such that fewer samples may be needed. In [66] Basso *et al.* present a model where they predict the energy consumption of electric vehicles using machine learning and use this to solve an EVRP. A similar approach can be used to predict delays in arrival and departure times.

Another example of how the computation time can be reduced of this model is to exclude actions that result in an infeasible model. So if the model becomes infeasible for a combination of an action from the set of actions that can be chosen from and a sample path at a decision epoch, that specific action does not have to be considered anymore in that decision epoch. This will result in a shorter computation time. In addition, it would be interesting to think of a way to determine the actions that result in an infeasible solution as soon as possible while looping over the actions in the set of actions that can be chosen and looping over all sample paths, at a decision epoch, such that these actions can be excluded early on in the iterative process.

Another point of discussion is that we cannot guarantee that all aircraft are towed (on time). We have not yet found a way to indicate what the probability is that aircraft are not towed on time, besides running a lot of experiments and analyzing the statistics. However, what we do know is that 2 hours prior to the scheduled arrival/departure, we know what the actual arrival/departure time will be. There are roughly 2 reasons why a model becomes infeasible, that is (1) an aircraft will arrive when there is no truck available with enough battery to tow it. (2) All trucks are towing other aircraft. As information arrives 2 hours prior to the scheduled arrival/departure time, a truck can charge its battery at least half-way full, if it starts to charge immediately when the information about the arrival time becomes known. And the second point is highly unusual, as we saw that only 3 trucks were needed to tow 50 aircraft on time when considering non-electric vehicles. The minimum amount of non-electric towing trucks needed depends only on whether trucks are available, as these do not have to charge. As we saw what only 3 truck were needed to tow 50 aircraft, it will be highly unusual that all electric trucks will be towing as we found that more electric trucks are needed compared to the non-electric truck case, such that there is no truck available to tow the aircraft that arrives in two hours.

Another point of discussion is the fact that we only allow trucks to be assigned to the 3 requests that need to be towed earliest from that moment in time. This reduces the size of the actions that can be chosen from each decision epoch significantly, however, this is an assumption that might affect the solution. On the other side, our results do not indicate that the set of actions that can be chosen from is defined as too small. In the ideal case, one would like trucks to be able to go to any request after they finished a tow.

Lastly, it is good to note that how this model can be improved, highly depends on the question that the user wants to answer. For example, if one wants to use this model to determine the minimal number of trucks needed, computation time is not that important. One can let this model run for many realizations of a possible day (by using historic data) and then determine the number of trucks one has to buy. However, if one wants to use this model to determine throughout the day what the truck schedule must be, this current model is not useful, as the computation time is sometimes longer than the time between the actual time between decision epochs. However, the model can be improved by giving it an initial schedule using the scheduled flight schedule and the deterministic model and let a model determine the changes needed in this initial schedule dynamically using the exogenous information that becomes available throughout the day. So the improvements needed to this model depend on the question that a user wants to answer.

5.7 Conclusions on the EVRP under Uncertain Arrival and Departure Times, using a Dynamic Approach

In conclusion, we have formulated a second model that describes an Electric Vehicle Routing Problem (EVRP) under uncertain arrival and departure times. This second model is a dynamic model, that uses the exogenous information about the actual arrival and departure times that becomes available throughout the day. In this Stochastic Sequential Decision Model (SSDM), we determine the set of trucks that a decision needs to be made for at every decision epoch. For these trucks, we determine the possible actions that can be chosen, for every truck. Then we determine what the expected total electricity costs are when each of these actions are chosen. The expected costs are calculated by solving the deterministic EVRP as introduced in Chap. 3, for many different sampled flight schedules. When an action is chosen, the state is updated and the decision-making process continues until all information about arriving/departing times is known, as a deterministic model remains.

It is found that the SSDM results in fewer trucks needed, compared to a Robust Optimization (RO)-based model. The total electricity costs of the SSDM and of the deterministic model are found to be similar for a flight schedule of 12 aircraft.

The computation time is found to be very long, such that results are only obtained for a small fleet of trucks (4 trucks) and a small number of aircraft (12 aircraft). The computation time for a flight schedule of 12 aircraft, towed by a fleet of 4 trucks, is more than 40 times the computation time needed for the deterministic model and the RO-based model. Improvements to the model are needed if this model is to be used to determine the daily operations of a fleet of electric trucks throughout the day in a practical scenario, as the computation time is too long.

Chapter 6

Conclusion

In this chapter, we conclude our research project by answering the research questions presented in Sec. 1.4.1.

Within this thesis, Electric Vehicle Routing Problems (EVRPs) are developed that describe the operations of electric towing trucks at an airport, minimizing the electricity costs, in an attempt to answer the research question,

" How can an adapted version of a vehicle routing problem describe the operations of electric towing trucks at an airport under uncertainty? "

As explained in Sec. 1.4.3, the goals of this thesis project are to develop both a model that can determine the operations of electric towing trucks by deterministic arrival/departure times, as well as a model that does so for uncertain arrival/departure times. The developed deterministic EVRP, as presented in Chap. 3, is a Mixed Integer Linear Program (MILP) that minimizes the electricity costs. This model consists of constraints regarding the routing of the trucks, the time trucks start to tow, and the battery load of the trucks. From solutions of the model, truck schedules can be obtained, describing the operations of electric towing trucks at an airport. We have found by comparing the EVRP to a Vehicle Routing Problem (VRP) of non-electric trucks, that significantly more electric trucks are needed to tow all aircraft on time, given the selected truck specifications, due to the charging time of the electric trucks of the EVRP. The deterministic model solves fast enough to determine the operations at a regional Dutch airport.

Two types of EVRP models have been developed that take the uncertainty of arrival/departure times of aircraft into account. Both models use scenarios of the delays to take the uncertainty into account. In Chap. 4, a Robust Optimization (RO)-based model is presented, where trucks are forces to arrive at the start location of the tow before the earliest sampled arrival/departure time of the aircraft. The trucks were scheduled to tow another aircraft or to return to the depot, after the latest sampled arrival/departure time. This resulted in more significantly more trucks needed to tow all aircraft within the time interval of the earliest and latest sampled arrival/departure time of every aircraft.

A dynamic model, a Stochastic Sequential Decision Model (SSDM), is developed in order to adapt the truck schedule according to the information about the actual arrival/departure times of aircraft throughout the day. This model makes decisions throughout the day about what trucks must do next while considering a set of actions that can be chosen from and sampled scenarios of the delays. The action that results in the minimal expected costs at the end of the day, considering all sample paths, will be chosen at each decision epoch.

The computation time of this model is significantly longer than that of the deterministic and the RO-based model. However, the SSDM presented in Chap. 5 was able to determine the operations of a fleet of 4 electric towing trucks that tow 12 aircraft throughout the day, of which the arrival/departure times were uncertain. The results of the SSDM show that fewer trucks may be needed compared to the RO-based model. Given the long computation time of the dynamic model, even for relatively small problems, improvements on this model are needed for it to be suitable for (major) airports.

In the next chapter, we elaborate on general points of discussion on the models presented in this thesis and share our vision on future research of EVRPs.

Chapter 7

Discussion and Future Work

We developed 3 different models that determine the operations of electric towing trucks at an airport, minimizing the total electricity costs. The results of these models are presented and discussed in Chap. 3-5. However, there are points of discussion not discussed yet. In this chapter, we would like to address these points of discussion and propose ways to improve the models by presenting our vision for future work. We will present these points of discussion in 3 different categories. We start with general points of discussion, these points are relevant for all models presented in this thesis. Then we continue by discussing the models that take the uncertainty in arrival and departure times into account. This chapter will be finalized with ideas to make the Electric Vehicle Routing Problems (EVRPs) more realistic for specific applications.

7.1 General Points of Discussion

In this section, we discuss general points of discussion that apply to all models presented in this thesis. The first and main point of discussion is that the found truck schedules highly depend on the *input parameters.* These input parameters include the battery capacity of the trucks, the charging speeds (and costs), the electricity used by the trucks to tow the aircraft, and the speed at which the trucks drive and tow. If we adjust the charging speeds or the costs, the found truck schedules may be different. This also holds for all other input parameters. One of the goals of this thesis was to develop a model that can determine the operations of a fleet of electric towing trucks while minimizing the electricity costs. As the input parameters differ from airport to airport and this study is not performed for a specific client, it was not the focus of this research project to find the most realistic input parameters. We have made many assumptions on these parameters. However, we have shown that we are able to develop EVRPs, but if one is going to use one of the presented models for a specific airport, one must revise the input parameters.

In addition, we highly recommend for future research to focus on a compact formulation of the deterministic model. If this model has a more compact formulation, which results in less computation time needed to solve models, this will also result in less computation time of the Robust Optimization (RO)-based model and the Stochastic Sequential Decision Model (SSDM). So improving the deterministic model by means of the computation time, will also result in a faster RO-based model and a faster SSDM.

In this thesis, we considered 3 charging speed options, with their corresponding charging costs. However, in reality more charging speeds might be possible. By introducing more charging speeds, the set of binary Decision Variable (DV) increases as well, resulting in a longer computation time. A possible option is to include bounded continuous DVs that represent the charging speed. This also includes finding a way to describe the electricity costs associated with the bounded continuous charging speed set. Therefore, it is of importance that future research on these types of models focusses on a compact formulation of the depots and the different charging speed options.

For this research project, we have fixed the charging speed options, but also the costs associated with the charging speed. However, in reality the electricity price may not be fixed. The electricity price may be dynamic, due to various reasons. For example, an airport may have made agreements with the electricity supplier on the electricity price over the day, but an airport may also have invested in solar panels where the supply of electricity varies over time, such that total electricity costs vary over time. In addition, the electricity price may also depend on the amount of electricity used in a period of time. For future research, it would be very interesting to implement the effect of dynamic electricity pricing to EVRP models as presented in this thesis.

At large airports, multiple depots will be present at different locations at an airport, as there might not be enough space to charge many trucks at the same location. So, if large airports will use the models presented in this thesis, the presence of multiple depots needs to be added to the EVRP. This can be done by expanding the set of depots. However, by expanding the set of depots, the number of binary DV will increase, which might result in a longer computation time. In addition, by introducing multiple physical depots, some of the constraints need to be revised. For example, the constraint stating that a truck may only leave a depot when it is present, Eq. 3.6, needs to be adjusted as this constraint is based on the fact that trucks start the day leaving the only depot that the model has. When multiple depots are considered, one needs to constrain trucks to be able to leave only the depot where they start at the beginning of the day.

Our last general recommendation is regarding the location of charging stations. Especially in an early stage of the transition to electric towing trucks, decision-makers need to decide where the charging stations will be placed. With the models presented in this thesis, it is possible to determine what the best location is, in terms of the lowest electricity costs. In reality, other factors might be of more importance when determining where the depots must be placed. For example, a depot is probably not located where there is no space for many trucks to be positioned while charging. But the models presented in this thesis can give an idea of the effect on the operations of the electric towing trucks when a depot is positioned at specific locations.

7.2 Discussion on Uncertainty in a EVRP

In Chap. 4 and Chap. 5 we discussed models that include uncertainty in arrival and departure times of aircraft. We have seen that delays may have a large impact on the operations of the electric towing trucks and also on the total electricity costs. So it is of high importance that more is known about this delay, such that this can be taken into account in a better/more suitable way for the specific delay behaviour at an airport. One of the advantages of the methods presented in this thesis is the fact that they use scenario sampling. Although we used a normal distribution where we sampled scenarios from, also historic data can be used by these methods as scenarios. This leads to the recommendation to have a better look at the delay of aircraft. For example, we know that if an aircraft arrives late, there is a high probability that it will also depart late again. Quantitative knowledge on the delay and on the dependence of early delays on delays later that day results in a schedule that is more robust to the actual arrival and departure times. Having a better understanding of the behaviour of the delays may also result in suitable heuristics that can be used. This might lead to a reduction in computation time. So it is important for future research to look at the behaviour of the delay in arrivals and departures.

In addition, as briefly mentioned in Chap. 5, it would be very interesting to have a look into machine learning techniques that can predict the delay of a certain aircraft. If predictions can be made, these can be used as scenarios for the RO-based and the SSDM. Especially, as the computation time of the SSDM is high, due to the large number of samples that need to be drawn, the computation can be reduced significantly if a good estimate can be determined for the actual arrival/departure time of an aircraft and the large number of samples can be reduced by good estimates.

One of the consequences of using electric towing trucks is that there will be more trucks at the airport, as the current taxiing process is not executed by trucks. So there will be an increase in traffic at the airport. Ground Service Handlers (GSH) let us know during our conversations, that the traffic at airports is (at least at Schiphol Airport) already busy. So the traffic will only get busier. This might lead to traffic jams and uncertainty in the driving times of the trucks. For future research, it is interesting to get an idea of the effect of the introduction of significantly more trucks at an airport and whether this will result in traffic jams and uncertainty in travel times. In addition, it would be interesting for airports to know whether new roads need to be paved in order to prevent these traffic jams and where these roads need to be placed.

7.3 Additional Ideas

The rise of the use of electric vehicles resulted in a record number of electric vehicles sold in 2020, resulting in over 10 million electric vehicles currently on the road in the world [67]. Considering that the rise of the use of electric vehicles started roughly in 2008, one can imagine that a lot has changed in the field of electric charging since then. Also in terms of rules, agreements, and goals, companies are stimulated (forced) to switch to electric vehicles. For example, package delivery services and supermarket suppliers want/need to switch to electric vehicles [68, 69]. As (some) packages need to be delivered in specific time-slots but, package deliverers may be subject to traffic jams or other delays, it is important to determine how this affects the operations of the electric vehicles. The models presented in this thesis could also be applied to describe how package deliverers must deliver the packages in electric vehicles. This emphasizes the importance and versatility of EVRPs and research performed on this topic. So, the type of models presented in this thesis can be used for many different applications (and companies) by adapting the input parameters.

An idea that is especially of interest for large trucks, like the towing trucks at an airport, is the idea of swapping batteries instead of charging the batteries while they remain in the truck. This has the advantage that trucks do not have to remain (for a long time) at the charging station while charging, and in addition, usually there is not a lot of space at an airport for trucks to be charged. This way it is also interesting to exploit the idea of swapping batteries. This will also lead to fewer trucks needed, as only more batteries need to be bought, instead of whole trucks. It would be of interest to know how this affects the operations of electric towing trucks. This requires models where the number of trucks and batteries is not the same. For such a model, the battery "operations" and the truck operations need to be determined. This can be done with an adapted version of the models presented in this thesis. For example, this can be done by introducing n depots, in the case of n batteries and keeping track of the battery load of a battery that is charging.

A last point of recommendation is looking into the effect of a limited number of charging stations at a depot. For decision-makers, it is important to know how many charging stations need to be built. During this thesis project, we have looked briefly into this and tried to implement constraints regarding a maximum number of trucks that can be charging at the same moment in time. However, we have found that this is not trivial and due to the limited time of this project, we have decided to stop looking into this. However, this is a very relevant question for decision-makers.

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Appendix A

The Electricity Usage of Electric Towing Trucks

In this Appendix, we explain in detail how the electricity used by an electric towing truck is estimated. A general description is given in Sec. 2.1.1.

A tow job differs when a taxi-in tow is performed or a taxi-out. The trip from the exit lane to a gate of an arriving aircraft is defined as a taxi-in, while the taxi trip for departing aircraft from the gate to the runway is defined as a taxi-out. The engines of an aircraft need to warm up during a taxi-out, while the engines of an aircraft need to cool down during a taxi-in. This results in a different electricity consumption of the towing truck for a taxi-in tow and a taxi-out tow, as the truck needs to provide different amounts of electricity to an arriving and a departing aircraft.

The total electricity needed for a tow job consists of two main processes: electricity needed for the actual driving or towing and electricity needed to supply aircraft electricity during the tow. For all processes, it is assumed that they require constant power over time. This results in the electricity needed for all processes to be dependent on the duration of the processes.

During a taxi-in, a truck needs to provide an aircraft electricity for on-board systems and air-conditioning. It is assumed that the engine cool-down takes 2.5 minutes. So the truck needs to provide electricity to an aircraft during the taxi-in for the total transportation time minus 2.5 minutes, as the engines provide an aircraft with electricity during the cool-down of the engines.

A taxi-out tow requires electricity for on-board systems, air-conditioning, and for the engine starter. Also, electricity is needed from the truck while an aircraft is released. It is assumed that it takes about 3 minutes to release an aircraft and to disconnect an aircraft from the Fixed Power Unit (FPU). Usually, an aircraft engine takes about 5 minutes to warm-up. During this time, the truck does not need to provide an aircraft with electricity. Lastly, the actual engine starter takes about 45 seconds to start the engines.

The power needed for each process depends on the type and size of the aircraft. The International Civil Aviation Organization (ICAO) categorizes aircraft according to size. For each aircraft type, an estimate can be made for the power needed for each aircraft type. For this research, we consider 3 types of aircraft: small, middle, and large aircraft. An overview of examples of aircraft that are categorized in a certain category is given in Tab. A.1.

Aircraft category	ICAO category	Aircraft example
Small	C	Boeing 737
Middle	D	Boeing 767
Large	E/F	Boeing 777 / Airbus A380

Table A.1: Overview of the categorization of all aircraft.

The power needed for air-conditioning depends on the outside temperature. When the outside temperature is higher than the desired temperature of an aircraft, electricity is needed to cool the aircraft, while heating is needed when the outside temperature is lower than the desired inside temperature. The minimum power is needed for an outside temperature of about 18 °C. The power needed to heat an aircraft while the outside temperature is 10 °C is about the same for cooling an aircraft when the outside temperature is about 20 °C. For this project, it is assumed that the outside temperature is always between 10 °C and 20 °C. An overview of the duration and power needed for each type of aircraft of each process during taxi-in and taxi-out is given in Tab. A.2. The duration is given in terms of the transport time, t_t minus the time the engines take over the process. The transportation time is the time a truck tows the aircraft. This transportation time depends on the distance travelled, as the towing speed is considered constant.

Taxi process	Process	Duration [min]	Power for each aircraft category [kW]		
			Small	**Middle**	**Large**
Taxi-in	On-board systems	t_t - 2.5	3.7	14.1	33.9
	Air-conditioning	t_t - 2.5	175	300	350
Taxi-out	On-board systems	t_t - 2	3.7	14.1	33.9
	Air-conditioning	t_t - 2	175	300	350
	Engine starter	0.75	384	783	783

Table A.2: Overview of the duration and power needed of processes during taxi-in and taxi-out tows, for small, middle and large aircraft.

The electricity used to tow an aircraft depends on the velocity and the weight of an aircraft. It is assumed that trucks drive with a constant velocity of 14 km/h when towing and 30 km/h when trucks are driving empty. The power per kg for a velocity of 14 km/h is considered as 2.75 W/kg and for 30 km/h, 5.9 W/kg. There is a difference in typical weight for taxi-in and taxi-out aircraft, as aircraft are lighter when they arrive as they used most their fuel during the flight already. Typical weights for taxi-out aircraft in the small, middle and large aircraft categories are, 80.000 kg, 200.000 kg and 575.000 kg respectively. For taxi-in aircraft, the typical weight per category is 65.000 kg, 130.000 kg, and 325.000 kg respectively. The electricity used for towing for each category is given in Tab. A.3.

Aircraft category	Power taxi-in [kW]	Power taxi-out [kW]
Small	180	220
Middle	360	550
Large	895	1580

Table A.3: Overview of the power needed for transportation of an aircraft during taxi-in and taxi-out tows, for small, middle and large aircraft.

Appendix B

Detailed Truck Schedule

In this Appendix, we present an example of what we consider as a detailed truck schedule. Throughout this thesis we present truck schedules by indicating when a truck is away from the depot, either towing or driving and we indicate when a truck is at the depot charging (and with what charging speed). However, the full truck schedule includes how a truck must drive, which aircraft it needs to pick-up and tow to what location etc etc. In this appendix, we explain what this detailed truck schedule looks like by an example.

Fig. B.1 shows a truck schedule of a fleet of 5 trucks that tow 16 flights. This schedule is obtained from solving the deterministic Electric Vehicle Routing Problem (EVRP) as presented in Chap. 3 with some maximum solving time. Tab. B.1 and Tab. B.2 present the detailed truck schedule. Tab. B.1 indicates the time at which a truck needs to leave the depot and at what time it starts to tow an aircraft and when it returns to the depot and for how long it charges at what charging speed. Tab. B.2 indicates the requests it will handle and which routes the trucks need to take during the trip. The nodes indicated in this table correspond to the nodes indicated in the aerodrome chart of Fig. B.2.

Let us look at the operations of truck 1 in detail. Tab. B.2 indicates that truck 1 makes 3 trips. The first trip is to tow the aircraft of request 12. Note that all arriving and departing requests are ordered such that the first half of the request numbers are arrivals (requests 0 to 7) and the second half of the request numbers are departing aircraft (requests 8 to 15). So the aircraft of request 12 is a departing flight. The first trip of truck 1 is from the depot (node 38) to the start location of request 12 (node 25) to the end location of request 12 (node 4) back to the depot (node 38). This truck leaves the depot at 7:15 o'clock and arrives at the start location (node 25) at 7:17 o'clock and tows the aircraft from node 25 (a gate) to node 4 (runway) and drives back to the depot and arrives there at 7:31 o'clock. The battery level at the start is 150 kWh, as we assume that all trucks are fully charged at the beginning of the day and the battery level after this first trip is 68.82 kWh. The truck is scheduled to charge with charging speed option 0 for 24.6 minutes such that the battery level is 68.62 kWh+15.38 kWh = 84.20 kWh. This is the battery level when the truck leaves for its second trip of the day. The truck is scheduled to go to start its second trip at 7:55 o'clock, which perfectly fits as it is scheduled to be done charging 24.6 minutes after it arrives at 7:31 o'clock, which is at 7:55 o'clock. Tab. B.2 indicates that the truck drives the shortest route.

During trip 2 of truck 1, the truck starts from the depot and tows the aircraft of request 15 to the runway and returns to the depot. This trip starts at 7:55 o'clock and the truck arrives at the start location (gate of node 31) of the tow at 7:56 o'clock and the truck arrives at the depot at 8:11 o'clock. The battery level of the truck is now 0 kWh. At the depot, truck 1 first charges with the charging speed of option 0 for 41 minutes and then switches to the charging speed of option 2, to charge for another 183.14 minutes. The total charging time after trip 2 is 224.14 minutes. In total it has charged 25.63 kWh+22.89 kWh = 48.52 kWh. This way, the battery level of truck 1 is at the start of trip 3 48.52 kWh.

After truck 1 is done charging after trip 2, it will start trip 3. Trip 3 starts 224 minutes after the truck arrived at the depot after trip 2, which was at 8:11 o'clock. 224 minutes after 8:11 o'clock is 11:55 o'clock. Truck 1 will go from the depot to the start location of request 3 (node 3, which is the landing lane as the aircraft of the request is an arrival), then it tows the aircraft to its gate (node 31), then the truck goes back to the depot. It arrives there at 12:06 o'clock and its battery is completely empty.

The same explanation can be done for all other trucks. All information on the truck schedules of the other trucks can also be found in Tab. B.1 and Tab. B.2. These detailed truck schedules are made for all truck schedules depicted in this thesis.

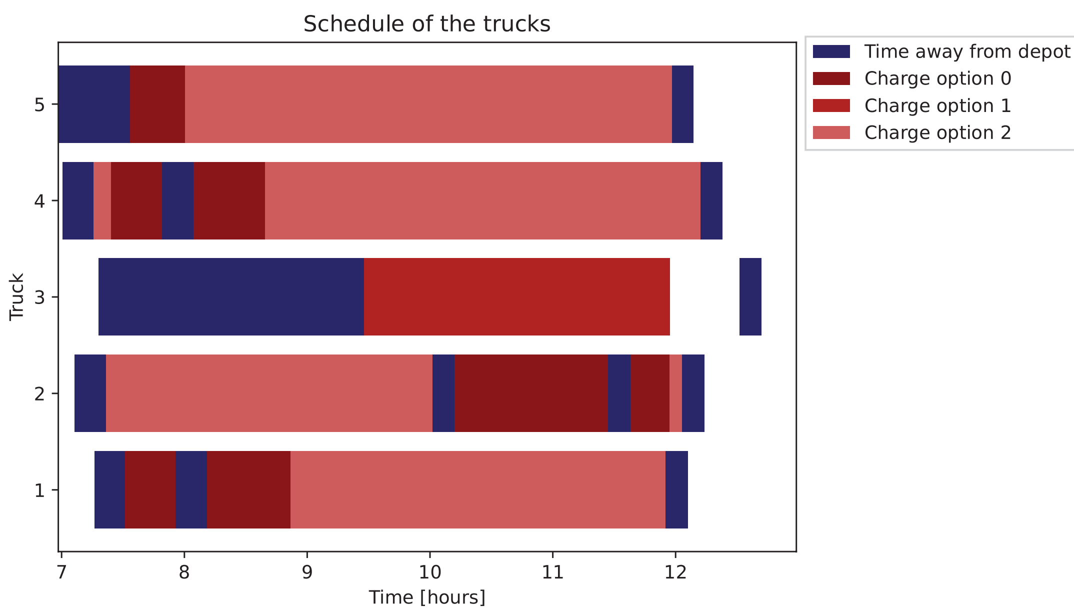


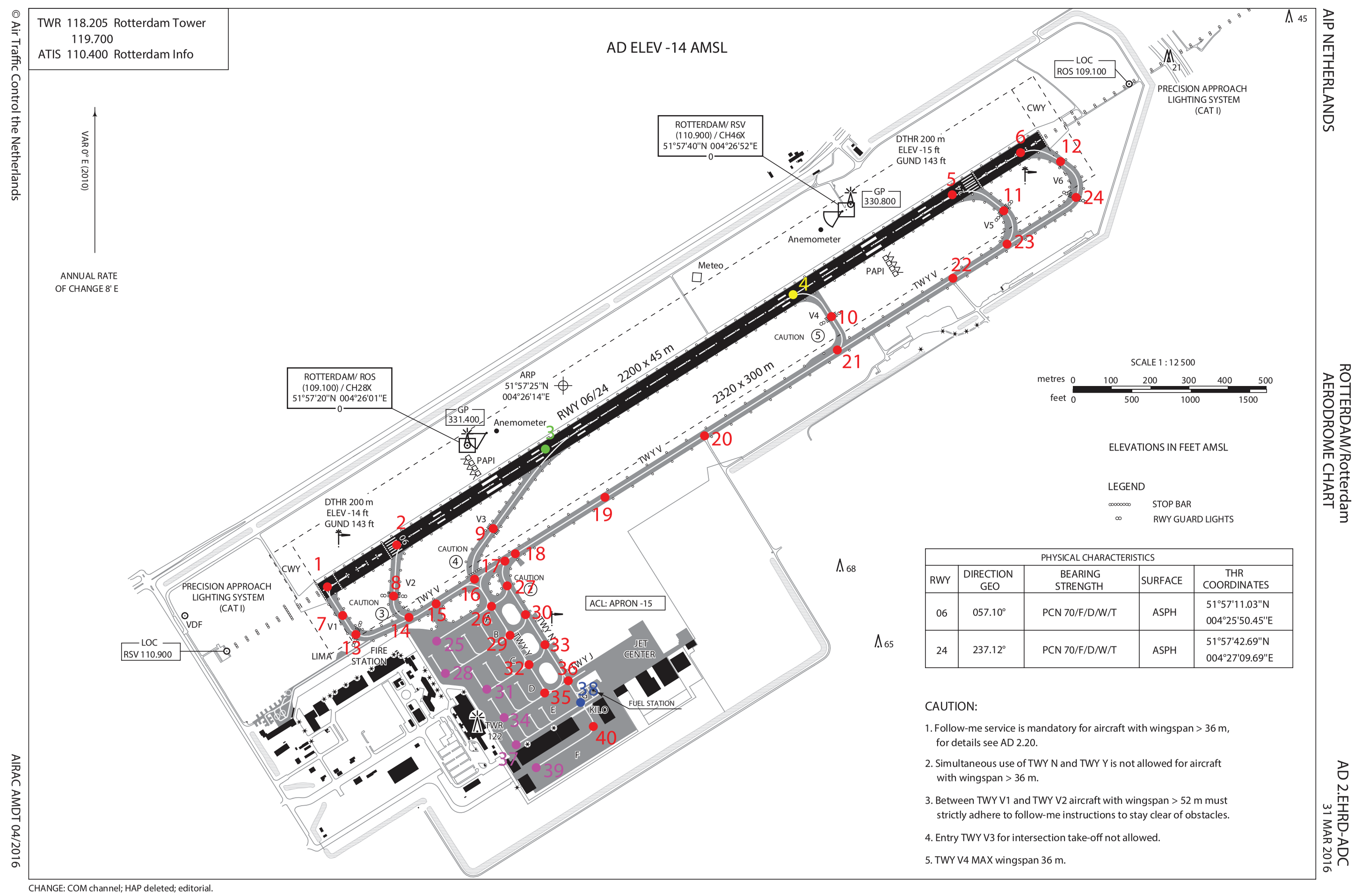
Figure B.1: Truck schedule of a fleet of 4 trucks of a flight schedule of 16 flights with 5 minutes of service time, determined by the deterministic EVRP explained in Chap. 3. The total electricity costs are € 1296.72.

Truck	Trip #	Time at D	Load at D	Time at i (= s_i)	Load at i (=q_i)	Time at D	Load at D	$Q1$	Q_t 1	$Q2$	Q_t 2
1	1	7.15	150.00	7:17	147.45	7:31	68.82	0	0	15.38	24.6
	2	7:55	84.20	7:56	82.64	8:11	0	25.63	41.00	22.89	183.14
	3	11:55	48.52	11:57	43.78	12:06	0	0	0	0	0
2	1	7:06	150.00	7:07	148.45	7:21	65.81	0	0	19.93	159.43
	2	10:01	85.74	10:03	81.00	10:10	37.22	0	0	46.99	75.19
	3	11:25	84.21	11:29	79.49	11:37	35.71	12.05	19.28	0.74	5.91
	4	12:02	48.52	12:05	43.78	12:14	0	0	0	0	0
3	1	7:18	150.00	7:19, 9:19	147.89, 72.20	9:28	28.42	0	0	18.67	149.37
	2	12:31	47.09	12:33	42.35	12:41	0	0	0	0	0
4	1	7:00	150.00	7:01	148.45	7:16	65.81	1.05	8.37	15.68	25.09
	2	7:49	82.53	7:50	80.43	8:04	0	21.97	35.15	26.58	212.61
	3	12:12	48.50	12:14	43.78	12:22	0	0	0	0	0
5	1	6:58	150.00	6:59, 7:19	148.45, 80.94	7:33	0.51	16.88	27.01	29.72	237.75
	2	11:58	47.11	12:00	42.35	12:08	0	0	0	0	0

Table B.1: Detailed truck schedule part 1 (out of 2). Here the first two columns indicate the truck and the trip number of each trip. A trip is considered as the route that starts and ends at the depot, a trip may consist of multiple aircraft towed. Columns 3 and 4 indicate the time a truck leaves the depot and the battery level it has when leaving the depot. Columns 5 and 6 indicate the time and the battery level of the truck when it arrives at a request. Column 7 and 8 indicate the time and battery level when a truck arrives at the depot (at the end of the trip). Columns 9-12 indicate the amount of electricity that is charged in kWh at the first time charging, the time this takes in minutes, the amount of electricity that is charged in kWh at the second time charging (when a truck can switch charging speeds), and the time this second time charging takes, respectively.

Truck	Trip #	*i*	Paths
1	1	12	[38, 36, 33, 30, 27, 26, 25], [25, 26, 16, 9, 3, 4, 4, 3, 9, 16, 17, 27, 30, 33, 36, 38]
	2	15	[38, 36, 33, 32, 31], [31, 32, 29, 26, 16, 9, 3, 4, 4, 3, 9, 16, 17, 27, 30, 33, 36, 38]
	3	3	[38, 36, 33, 30, 27, 17, 16, 9, 3], [3, 9, 16, 26, 29, 32, 31, 31, 32, 33, 36, 38]
2	1	10	[38, 36, 33, 32, 31], [31, 32, 29, 26, 16, 9, 3, 4, 4, 3, 9, 16, 17, 27, 30, 33, 36, 38]
	2	1	[38, 36, 33, 30, 27, 17, 16, 9, 3], [3, 9, 16, 26, 29, 32, 31, 31, 32, 33, 36, 38]
	3	2	[38, 36, 33, 30, 27, 17, 16, 9, 3], [3, 9, 16, 26, 29, 32, 31, 31, 32, 33, 36, 38]
	4	5	[38, 36, 33, 30, 27, 17, 16, 9, 3], [3, 9, 16, 26, 29, 32, 31, 31, 32, 33, 36, 38]
3	1	11, 0	[38, 36, 33, 30, 29, 28], [28, 29, 26, 16, 9, 3, 4, 4, 3], [3, 9, 16, 26, 29, 32, 31, 31, 32, 33, 36, 38]
	2	7	[38, 36, 33, 30, 27, 17, 16, 9, 3], [3, 9, 16, 26, 29, 28, 28, 29, 30, 33, 36, 38]
4	1	9	[38, 36, 33, 32, 31], [31, 32, 29, 26, 16, 9, 3, 4, 4, 3, 9, 16, 17, 27, 30, 33, 36, 38]
	2	14	[38, 36, 33, 30, 29, 28], [28, 29, 26, 16, 9, 3, 4, 4, 3, 9, 16, 17, 27, 30, 33, 36, 38]
	3	6	[38, 36, 33, 30, 27, 17, 16, 9, 3], [3, 9, 16, 26, 29, 32, 31, 31, 32, 33, 36, 38]
5	1	8, 13	[38, 36, 33, 32, 31], [31, 32, 29, 26, 16, 9, 3, 4, 4, 3, 9, 16, 26, 29, 28], [28, 29, 26, 16, 9, 3, 4, 4, 3, 9, 16, 17, 27, 30, 33, 36, 38]
	2	4	[38, 36, 33, 30, 27, 17, 16, 9, 3], [3, 9, 16, 26, 29, 28, 28, 29, 30, 33, 36, 38]

Table B.2: Detailed truck schedule part 2 (out of 2). Here an overview of the actual routes that the trucks need to drive during the trips. The first and second column indicate the truck and the trip number. The third column indicates which requests are handled during the trip. And the fourth column indicates the nodes that are visited during that trip. The nodes correspond to the number at the graph of the aerodrome chart of Fig. B.2. The node numbers between square brackets indicate the nodes corresponding to a single binary Decision Variable (DV).



RWY	DIRECTION GEO	BEARING STRENGTH	SURFACE	THR COORDINATES
06	057.10°	PCN 70/F/D/W/T	ASPH	51°57'11.03"N 004°25'50.45"E
24	237.12°	PCN 70/F/D/W/T	ASPH	51°57'42.69"N 004°27'09.69"E

Figure B.2: Aerodrome chart of Rotterdam Airport. The graph that is used throughout this thesis, including the node numbers of the graph. The green node is the landing lane, the yellow node is the runway, and the pink nodes are the gates.

Appendix C

Flight Schedule

Table C.1: Flight schedule of 2 days at the Rotterdam Airport. The traffic type 'D' represents departing flights and 'A' indicates an arriving aircraft.

Flight Number	Actual Local	Scheduled Local	Traffic Type
TRA5691	07:04	06:55	D
TRA6035	07:06	07:00	D
TRA6061	07:12	06:55	D
CFE4450	07:14	07:05	D
TRA5701	07:22	07:05	D
TRA6421	07:24	07:10	D
TRA-731	07:45	07:35	D
TFL-585	07:53	07:20	D
TRA5367	08:00	07:55	D
TRA5021	08:22	08:00	D
CFE4451	09:24	09:25	A
CFE4452	10:05	09:55	D
CFE4453	10:08	10:15	A
CFE4454	10:49	10:50	D
TRA6422	11:24	11:35	A
TRA6062	11:52	11:55	A
TRA6036	11:55	12:15	A
TRA5204	12:00	12:15	A
TRA5692	12:09	12:20	A
TRA5689	12:26	12:25	D
TRA5052	12:28	12:40	A
TRA6191	12:44	12:40	D
PGT1641	13:04	13:00	A
TRA5987	13:06	13:00	D
TRA6081	13:08	13:05	D
TFL-586	13:13	12:50	A
CFE4477	13:21	13:30	A

Flight Number	Actual Local	Scheduled Local	Traffic Type
TRA5051	13:39	13:25	D
TRA5702	14:04	13:55	A
CFE4476	14:13	14:05	D
TRA5022	14:17	14:25	A
TRA6841	14:22	14:00	D
TFL-765	14:26	13:50	D
PGT1642	14:52	13:40	D
CFE4455	15:01	15:05	A
TRA5368	15:44	15:45	A
TRA6783	15:46	15:30	D
CFE4456	15:52	15:45	D
TRA6093	15:55	16:00	D
TRA-732	16:05	16:05	A
CFE4479	16:35	16:40	A
TRA6082	16:41	16:40	A
TRA5023	16:43	16:30	D
TRA5988	16:49	17:00	A
CFE4478	17:19	17:15	D
TRA5053	17:32	16:50	D
TRA5690	17:43	17:50	A
TRA5203	17:54	17:45	D
TRA6192	18:01	18:00	A
TRA6441	18:10	17:35	D
CFE4457	18:28	18:35	A
TRA5067	18:47	18:35	D
TRA5293	18:55	18:40	D
CFE4458	19:33	19:15	D
TRA6784	21:34	21:45	A
CFE4459	21:45	21:40	A
TRA6842	21:48	22:00	A
TFL-766	22:33	22:30	A
TRA6094	22:36	22:30	A
TRA5024	22:54	22:55	A
TRA5068	22:56	22:55	A
TRA5294	22:58	22:40	A
TRA6442	23:20	22:50	A
TRA5054	23:31	22:35	A
TRA5689	07:09	06:55	D
TRA5639	07:14	06:55	D
CFE4450	07:17	07:05	D
TRA6061	07:21	07:05	D
TRA5643	07:25	07:10	D
TRA6485	07:27	07:15	D
TRA6697	07:38	07:20	D
TRA6091	07:57	07:45	D
TRA5033	08:00	07:55	D
TFL-545	08:10	07:55	D
FHM6021	08:55	08:45	D
TRA6698	11:40	12:10	A
TRA6062	12:09	12:05	A

Flight Number	Actual Local	Scheduled Local	Traffic Type
TRA6486	12:26	12:30	A
TRA6259	12:49	12:45	D
TRA5640	12:55	13:05	A
PGT1261	13:03	13:00	A
TRA6191	13:05	12:55	D
TRA5644	13:23	13:20	A
TRA5833	13:24	13:15	D
TRA6285	13:38	13:30	D
TRA5034	13:48	14:00	A
PGT1262	13:58	13:45	D
TRA6081	14:17	14:05	D
TRA6092	14:27	14:15	A
TRA6093	14:55	12:20	D
TRA6094	15:13	11:35	A
TRA6325	16:01	16:00	D
TRA6260	17:23	17:40	A
TRA6286	17:36	17:50	A
FHM6022	17:40	17:35	A
TRA6082	17:44	17:40	A
TRA5688	18:00	18:00	A
TRA6192	18:14	18:15	A
TFL-546	18:17	18:45	A
TRA5690	18:30	18:45	A
TRA5067	18:33	18:25	D
TRA6421	18:43	18:30	D
TRA5997	18:52	18:40	D
TRA5243	18:55	16:00	D
TRA5687	19:08	18:55	D
TRA5021	19:10	18:55	D
TRA5053	19:34	19:30	D
LMU6312	20:27	20:15	A
TRA6326	21:46	22:05	A
LMU6313	22:18	21:15	D
TRA5068	22:31	22:45	A
TRA5998	22:39	22:55	A
TRA6422	22:42	22:50	A
TRA5834	22:44	22:55	A
TRA5054	22:53	22:55	A
TRA5022	23:03	22:45	A

Appendix D

Robust Optimization versus Stochastic Programming

In Chap. 4 we present a Robust Optimization (RO)-based model that describes how the optimal operations of a fleet of electric towing trucks under uncertain arrival and departure times, can be determined. However, the RO-based model is not the only technique that can be used to describe the operations of electric towing trucks under uncertain arrival/departure times. Powell discusses in "A unified framework for stochastic optimization" [70] how all methods in stochastic optimization can be categorized and how for many problems, one can describe a problem by various "types" of stochastic optimization problems.

Powell discusses that RO is the robust analog of a stochastic search problem. In this Appendix, we show that the RO-approach of an Electric Vehicle Routing Problem (EVRP) under uncertain arrival and departure times, as presented in Chap. 4, can be described as a *Stochastic Program*.

A Stochastic Program (SP) is described in stages and the most simple version of a mixed-integer SP is a two-stage SP. A two-stage maximization SP is defined as,

$$\begin{aligned} \max_{x \in \mathbb{R}^n} \quad & f^T x + E_\xi [Q(x,\xi)] \\ \text{s.t.} \quad & Ax \leq b \\ & x_i \in \mathbb{Z}, \quad \forall i \in I, \end{aligned} \tag{D.1}$$

where $Q(x,\xi)$ is the optimal value of the second-stage problem,

$$\begin{aligned} \max_{y \in \mathbb{R}^m} \quad & q(\xi)^T y \\ \text{s.t.} \quad & T(\xi)x + W(\xi)y \leq h(\xi) \\ & y_i \in \mathbb{Z}, \quad \forall i \in I'. \end{aligned} \tag{D.2}$$

Here $x \in \mathbb{R}^n$ is the vector containing all Decision Variables (DVs) of the first-stage problem and $y \in \mathbb{R}^m$ the second-stage DV vector. ξ represents the uncertain data. The first-stage problem can be considered as the "here and now", as a decision needs to be made "now", before we know what the realization of the uncertain data ξ will be. The second stage can be considered as the moment in time, where the uncertain information becomes available and we need to optimize for the realized scenario.

In order to further explain the idea of the first and second stage, we present *the farmer's problem*. Consider a farmer that grows different crops. And at the beginning of the year, he has to decide how much of his land he grows which crop in order to maximize his profit. He needs a certain amount of each crop for his own use and he can sell the surplus and he can buy crops if he did not harvest enough of each crop for his own use. However, the amount of crops that he can harvest for each crop is dependent on the weather. Consider that the weather can be described by a finite number of realizations. For example, a number of realizations sampled from a distribution that describes the weather (for a period of time). So the weather is uncertain and the farmer does not know how many crops he will harvest at the end of the year. But he needs to decide now how much land he grows each crop.

This problem can be described as a SP. The decision of how much land the farmer needs to grow each crop can be described by the stage 1 DVs, x, and the number of crops he will sell and how many crops he needs to buy given a certain realization (scenario) of the weather of last year, is determined in the second stage by the DVs, y.

In the case of a finite number of scenarios, the decisions made in stage 1 need to be valid in every scenario, while the decisions made in stage 2 are specific for each scenario. If we would like to describe an EVRP with uncertain arrival and departure times, there would be 2 options. The first option is to only have DVs in stage 1. In this case, we make a schedule at the beginning of the day, that needs to minimize the electricity costs, while all aircraft of the sampled scenarios are towed on time. No decisions need to made after we know what the actual realization of the flight schedule is, as by the time we know the arrival and departure times of all aircraft, it is the end of the day and no decisions need to be made. This approach is very similar to the RO-approach described in Chap. 4.

The second option is a multi-stage SP. In this case we set different moments in time as the first, second, third etc. stage. This will be similar to a Stochastic Sequential Decision Problem (SSDP) with deterministic decision epochs. The implementation of a Stochastic Sequential Decision Model (SSDM) as a multi-stage SP will be difficult, as one needs to determine which DVs belong to which stage before one starts to solve, while the arrival/departure times are uncertain.

So in conclusion, if we would describe an EVRP with uncertain arrival and departure times as a SP, there are two options, (1) all DVs would be stage 1 DVs and the schedule is determined at the beginning of the day. This model will be similar to our RO-approach of Chap. 4. Or (2) a multi-stage SP model can be formulated, which will be similar to our SSDM of Chap. 5. So we agree with Powell, that problems can be described by different approaches and that they might end up being very similar.

Appendix E

Additional Results of the RO-Based Model

In this Appendix, we present additional results obtained from the Robust Optimization (RO)-based model as presented in Chap. 4. Every time we run this model, the sampled flight schedules will be slightly different, as the scheduled flight schedule remains the same, but the sampled delays differ from sample path to sample path. This results in different truck schedules found every run by the RO-based model. In this Appendix, we show that indeed the found truck schedules are different and we briefly discuss the found truck schedules. The goal of this Appendix is to show that indeed the obtained truck schedules differ and that the developed model works as expected. This Appendix does not contain statistics on the obtained results.

We have performed a total of 12 runs of this model. From these 12 runs, 3 runs resulted in an infeasible model. For these runs, sampled realizations of the arrival/departure times of a certain request led to the infeasibility of the model. The result of the first run of the RO-based model is presented and discussed in Sec. 4.4. The results of the other 8 feasible models are presented in this Appendix.

Fig. E.1 and Fig. E.2 show the additional truck schedules obtained from the RO-based model. The truck schedules show that indeed the best-found truck schedules are different as for every run, 300 different sample paths are sampled from the delay distribution. We ordered the truck schedules by total electricity costs, so the truck schedule of Fig. E.1a has the highest total electricity costs and the truck schedule of Fig. E.2d the lowest total electricity costs. The total electricity costs of these truck schedules are of the same order of magnitude. The difference in the total electricity costs is due to the fact that in some truck schedules more time needs to be charged with the charging speed of option 0 or option 1, compared to others. These truck schedules have higher total electricity costs. This can be seen by the fact that the trucks of the truck schedule of Fig. E.1a need to charge more with option 0 and option 1, compared to the trucks of the truck schedule of Fig. E.2d.

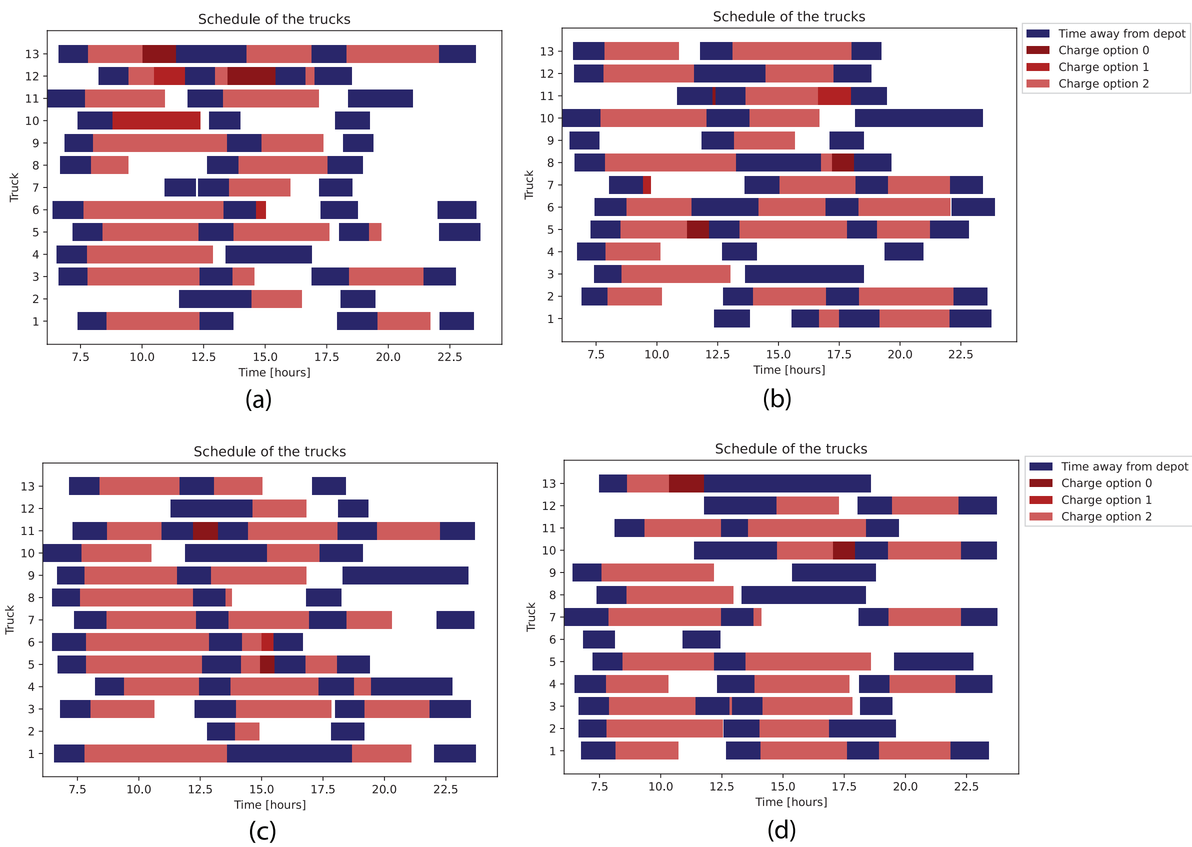


Figure E.1: Additional truck schedules obtained from the RO-based model (option 2) as presented in Chap. 4. Truck schedules of 13 trucks that serve 50 aircraft, where 300 sampled delays per request are considered. The total electricity costs are in **(a)** € 3186.24, **(b)** € 3119.09, **(c)** € 3116.14, **(d)** € 2985.98.

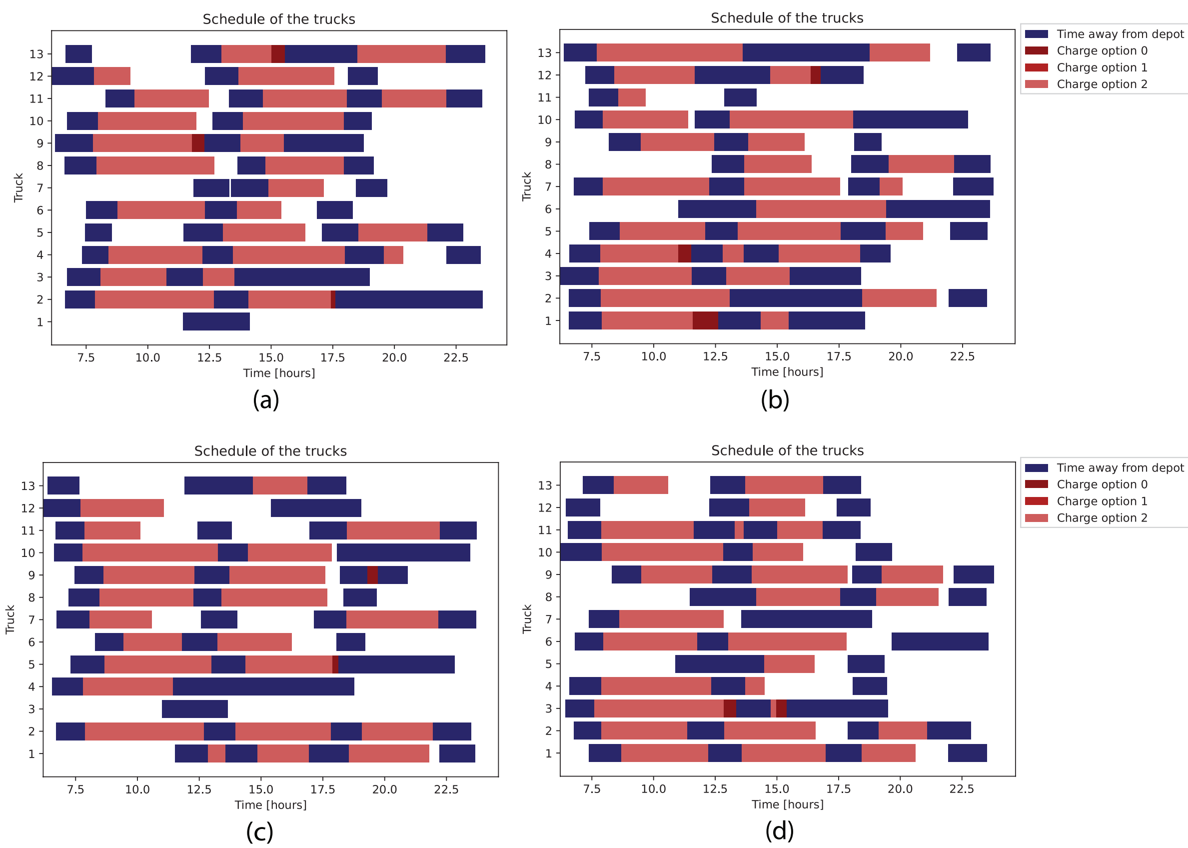


Figure E.2: Additional truck schedules obtained from the RO-based model (option 2) as presented in Chap. 4. Truck schedules of 13 trucks that serve 50 aircraft, where 300 sampled delays per request are considered. The total electricity costs are in **(a)** € 2968.23, **(b)** € 2950.78, **(c)** € 2888.41, **(d)** € 2834.13.

Appendix F

Additional Results SSDM

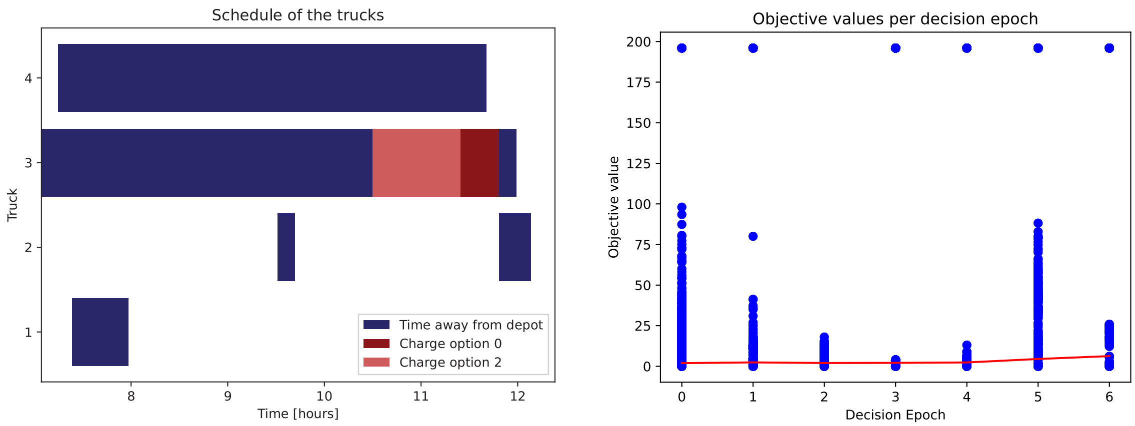
In this Appendix, we present additional results obtained from the Stochastic Sequential Decision Model (SSDM) as presented in Chap. 5. Every time we run this model, the "actual" flight schedule will be different, resulting in different truck schedules found by the SSDM. In this Appendix, we show that indeed the found truck schedules are different and we briefly discuss the found truck schedules and the objective values found for all iterations of the Mixed Integer Linear Program (MILP) of the found truck schedule. We need to emphasize that for the results of the Robust Optimization (RO)-based models, like presented in Appendix E, the considered scheduled flight schedule is the same for all runs. The only the difference between the runs are the earliest and latest sampled arrival/departure times for every request, such that the total time a truck is scheduled to tow an aircraft differs per run for every request. So we need to emphasize, that for the results of the SSDM presented in this Appendix, the realization of the flight schedule differs per run.

The goal of this Appendix is to show that indeed for every run, the realization of the flight schedule is different and thus also the corresponding found truck schedule. This Appendix does not contain statistics on the obtained results.

We have performed a total of 5 runs of this model, the results of the first run of the SSDM is presented and discussed in Sec. 5.6 and the corresponding truck schedule is given in Fig. 5.3a. The results obtained from the other 4 runs are presented in this Appendix.

The truck schedules of Fig. F.1a, Fig. F.2a, Fig. F.3a, and Fig. F.4a are quite similar. We see for all schedules about 12 decision epochs are needed until all information becomes available. The expected costs at every decision epoch increases and decreases slightly from decision epoch to decision epoch, this is due to exogenous information that becomes available. We do not see any significant sudden increase or decrease of the expected electricity costs.

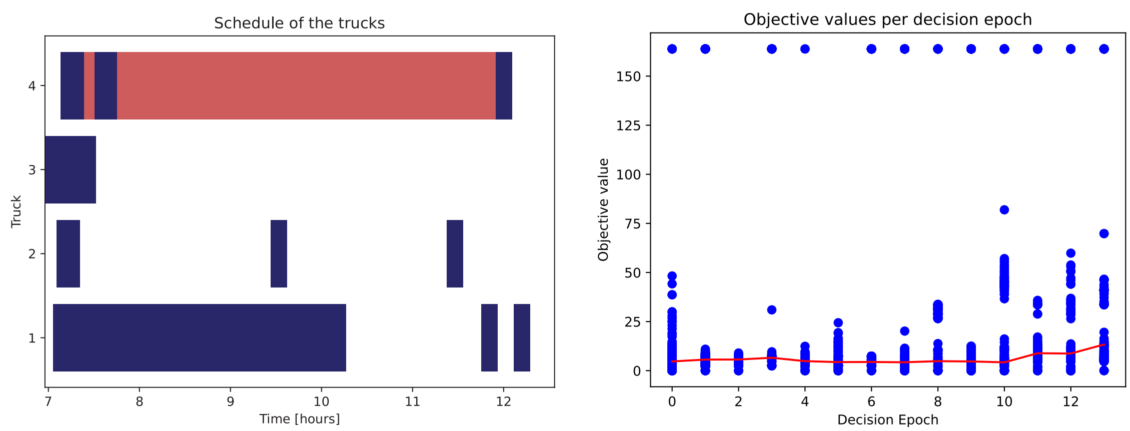
In Fig. F.1a, we see an obtained best-found solution of a truck schedule of 4 trucks that tow 12 aircraft during that day. A remarkable point to notice about this truck schedule, is that after 6 decision epochs all exogenous information about the arriving/departing had arrived, so only 6 decision epochs were needed. This is as only a few decisions are made until about 10 o'clock, which is around the moment in time the information about the latest scheduled flight becomes available, such that a deterministic model remains and the sequential decision making process stops. Note that at each decision epoch, actions for multiple trucks can be chosen.



(a) Truck schedule determined by a SSDM

(b) Objective values of all combinations of actions and sample paths

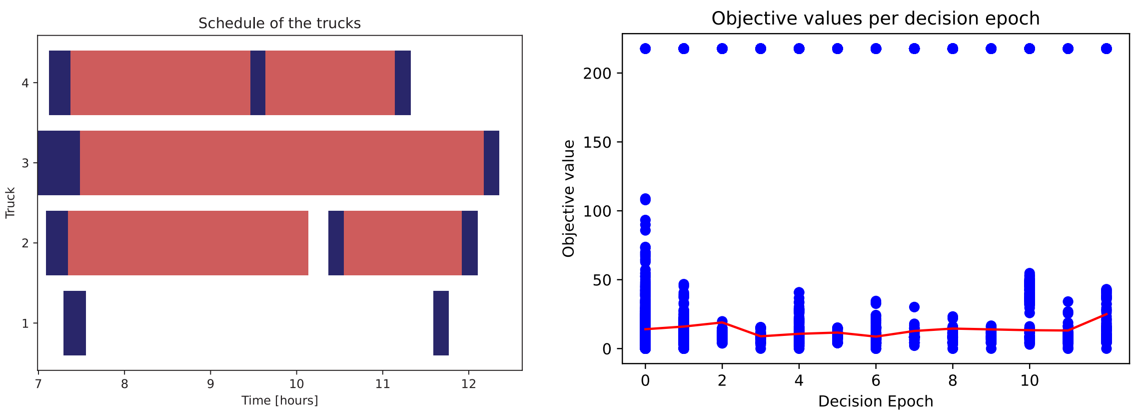
Figure F.1: **(a)** A best-found truck schedule of 4 trucks that tow 12 aircraft, of which the arrival times are uncertain, by a SSDM. The total electricity costs are € 850.41. **(b)** The objective values of every combination of the actions that can be chosen from at each decision epoch for every sample path. The red line indicates the expected charging costs for the action that is chosen in that decision epoch.



(a) Truck schedule determined by a SSDM

(b) Objective values of all combinations of actions and sample paths

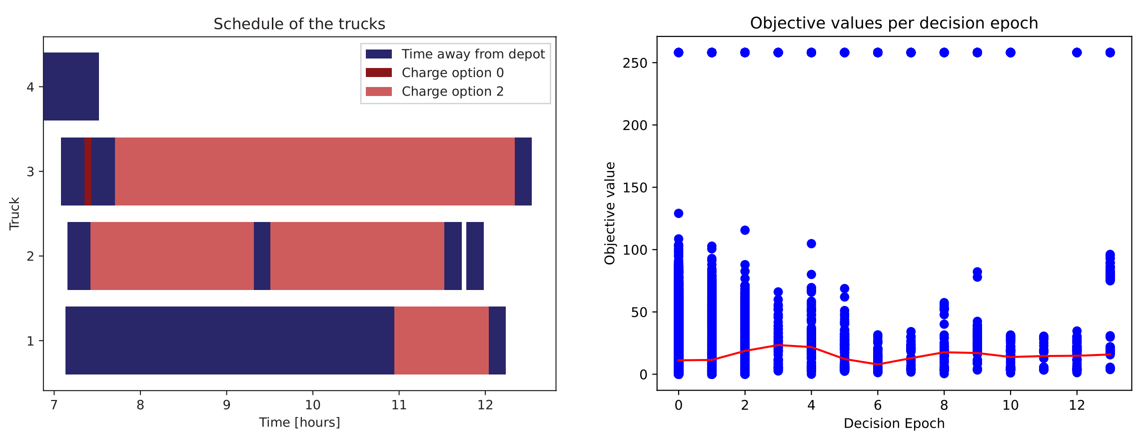
Figure F.2: **(a)** A best-found truck schedule of 4 trucks that tow 12 aircraft, of which the arrival times are uncertain, by a SSDM. The total electricity costs are € 833.92. **(b)** The objective values of every combination of the actions that can be chosen from at each decision epoch for every sample path. The red line indicates the expected charging costs for the action that is chosen in that decision epoch.



(a) Truck schedule determined by a SSDM

(b) Objective values of all combinations of actions and sample paths

Figure F.3: (a) A best-found truck schedule of 4 trucks that tow 12 aircraft, of which the arrival times are uncertain, by a SSDM. The total electricity costs are € 866.99. **(b)** The objective values of every combination of the actions that can be chosen from at each decision epoch for every sample path. The red line indicates the expected charging costs for the action that is chosen in that decision epoch.



(a) Truck schedule determined by a SSDM

(b) Objective values of all combinations of actions and sample paths

Figure F.4: (a) A best-found truck schedule of 4 trucks that tow 12 aircraft, of which the arrival times are uncertain, by a SSDM. The total electricity costs are € 843.39. **(b)** The objective values of every combination of the actions that can be chosen from at each decision epoch for every sample path. The red line indicates the expected charging costs for the action that is chosen in that decision epoch.