Optimizing towing processes at airports

Jia Yan Du

TECHNISCHE UNIVERSITÄT MÜNCHEN

FAKULTÄT FÜR WIRTSCHAFTSWISSENSCHAFTEN -
LEHRSTUHL FÜR OPERATIONS MANAGEMENT

Optimizing towing processes at airports

Dipl.-Kffr. Univ. Jia Yan Du

Vollständiger Abdruck der von der Fakultät für Wirtschaftswissenschaften der Technischen Universität München zur Erlangung des akademischen Grades eines

Doktors der Wirtschaftswissenschaften
(Dr. rer. pol.)

genehmigten Dissertation.

Vorsitzender: Univ.-Prof. Dr. Martin Grunow
Prüfer der Dissertation:
1. Univ.-Prof. Dr. Rainer Kolisch
2. Univ.-Prof. Dr. Jens O. Brunner, Universität Augsburg

Die Dissertation wurde am 19.12.2013 bei der Technischen Universität München eingereicht und durch die Fakultät für Wirtschaftswissenschaften am 15.03.2014 angenommen.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

The number of aircraft movements is expected to increase by 50% in Europe from 2012 to 2035. The capacity at airports will be the bottleneck limiting future growth. Up to 12% of the demand in 2035 will not be satisfied (see EUROCONTROL [34]). Airports face the challenge of improving efficiency in order to cope with increasing demand while fully exploiting available resources. In the recent past, capacity constraints and cost pressure tightened flight schedules. This threatens smooth operations and punctuality. A primary source of delays are disruptions in the turnaround process. According to EUROCONTROL [33] the turnaround process accounted for 36% of delays at European airports in 2011. This work is dedicated to towing activities as one of the major steps in the turnaround process. This chapter introduces the towing process and the operational and strategic planning problem of towing service providers. Finally, it lays out the structure of the thesis.

1.1 Towing processes at airports

Planes do not have a reverse gear, so they need assistance to leave the parking position. They can use their own engines to move forward on the ground. However, over long distances towing is often more economical and ecological (see Airport Authority Zürich Airport [2]). Towing is distinguished between push-back, repositioning and maintenance towing.

- **Push-back**. The plane with the passengers (or cargo) on board is pushed backwards from its parking position (e.g. the gate) to the taxiway. From there the plane can move on its own to the runway for take off.

- **Repositioning**. The empty plane is towed from one parking position to another. For instance, a repositioning takes place if an occupied gate must be used by an incoming flight. Normally, the blocking plane has ample time before departure.
- **Maintenance towing**. The empty plane is towed to the hangar area for maintenance or repairs.

There are two main categories of tractors to carry out the jobs: tractors with and without a towbar. Towbar tractors connect with the plane via a towbar. Towless tractors raise the front part of a plane and position it on the tractor itself (see Kazda and Caves [40]). The largest towless tractor currently on the market is the Goldhofer AST 1X. Equipped with two 680 horsepower diesel engines, the tractor is capable of towing the 560-tonne A380 (see Goldhofer AG [36]). Towbar tractors usually are more flexible with respect to compatibility with plane types and have lower maintenance and investment costs compared to towless tractors. However, each plane type requires a different tow bar. Therefore, towbar tractors must return to a depot to change the towbar between two jobs in case of different plane types. Furthermore, a second person (e.g. the pilot) must be present in the cockpit while the plane is towed by a towbar tractor.

In this thesis I investigate the optimization of towing processes taking the perspective of a towing service provider. Operating costs as well as investment costs of towing tractors are high. Investment costs can reach around 1 million Euro per tractor (see Deutsche Lufthansa AG [27]). A towing service provider faces two key questions (see Figure 1.1):

1. Operational planning problem: What is the cost optimal assignment of towing jobs to towing tractors in daily operations? The towing service provider is responsible for carrying out all towing jobs on time. The assignment of tractors to towing jobs is part of their daily operations. Today most towing service providers apply manual planning tools, often resulting in inefficient schedules. The assignment significantly impacts service quality, as well as operating costs. In the short-term the available fleet for the assignment is given by the existing tractors.

2. Strategic planning problem: What is the cost optimal fleet composition and respective (dis-)investment strategy? On a strategic level the towing service provider is responsible for deciding on the fleet size and mix and thereby determining in each period how many tractors are

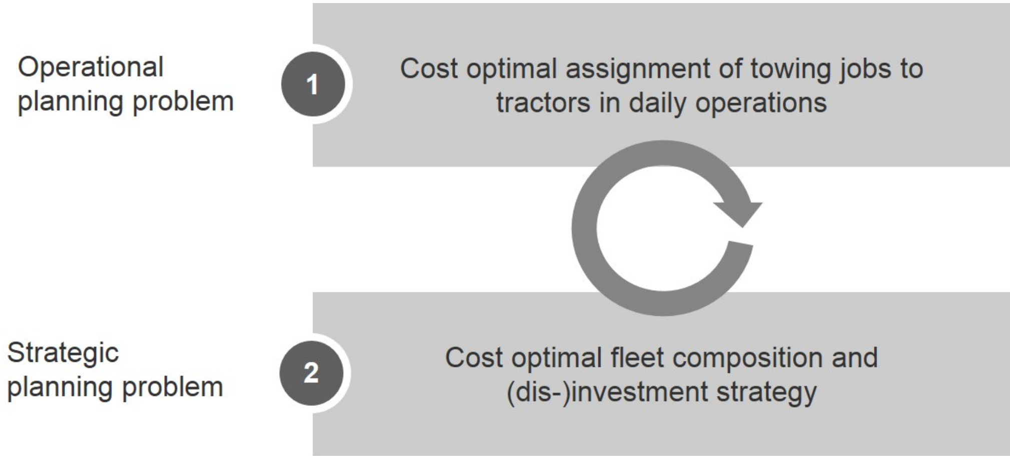

Figure 1.1: Operational and strategic planning problem of towing processes at airports

to be bought, overhauled or sold. This decision impacts investment costs, operating costs, as well as the service level.

Both planning problems are interlinked. An optimized tractor fleet, which can be influenced by tackling the strategic planning problem, allows for more efficient schedules in daily assignments. An efficient assignment, which is addressed in the operational planning problem, can reduce the number of tractors required, i.e. impacts the fleet size. Hence, both problems need to be examined in order to optimize towing processes from a holistic perspective. This thesis addresses both the operational and the strategic planning problem of towing processes at airports.

1.2 Structure of the thesis

The thesis contains four chapters. Chapter 1 introduces towing processes at airports, the related planning problems and the structure of the thesis. The two core chapters address the planning of towing processes from an operational perspective (Chapter 2) and from a strategic perspective (Chapter 3). Chapter 2 introduces a vehicle routing based scheduling model. I present a column generation heuristic as solution procedure and examine its performance in a computational study. A case study demonstrates how the model can be applied as a tool for identifying cost drivers and evaluating the efficiency of manual schedules in retrospect. The case study aims to derive insights which support schedulers in their future work. This chapter is based on Du et al. [30]. Chapter 3 addresses the problem of a cost minimal fleet composition. A model is introduced which supports towing service providers in their strategic investment decision. In a case study, a multi-period fleet (dis-)investment plan is derived for a towing service provider at a major European airport. Furthermore, a 4-step approach to aggregate demand based on flight schedule information is presented. In several scenarios I analyze the impact of demand, flight schedule disruptions and cost structures on the optimal fleet and conclude on the robustness of the investment plan with respect to these factors. This chapter is based on Du et al. [29]. The work concludes with the main findings and a discussion on potential directions for future research in Chapter 4.

Chapter 2

Scheduling of towing processes

In this chapter, I introduce a model that assigns tractors to towing jobs in order to minimize costs from perspective of a towing service provider. The assignment is subject to various operational restrictions and airport dependent specifications. For instance, technical compatibility with plane types and specific variable costs are associated with different tractor types. Furthermore, the time window to start the push-back is linked to the plane departure time, i.e. the service must take place during a fixed time window. Penalty costs occur if the push-back is delayed. Multiple depots to which tractor drivers can return for work breaks are considered. This implicates multiple uses of tractors in one planning period.

The remainder of this chapter is organized as follows: In the following, I provide an overview of push-back literature in the first part and literature on vehicle routing problems (VRP) in the second part. Section 2.2 introduces a mixed integer programming (MIP) formulation for the problem, followed by a description of the column generation heuristic (see Section 2.3). Computational experiments using real-world data from a major European airport are presented in Section 2.4. In Section 2.5 I discuss the results of a case study. This chapter concludes with a summary of the main findings in Section 2.6.

2.1 Related literature

The model formulation is based on the vehicle routing problem (VRP). Since the capacity constraint is negligible, the problem is also referred to as the multiple traveling salesman problem (mTSP), e.g. see Toth and Vigo

[60] and Laporte [44]. The problem considered can be categorized as an asymmetric mTSP with time windows, multiple trips, multiple depots and a heterogeneous fleet.

Operations research is widely applied in the air transport industry. Typical application areas are schedule design, fleet assignment and crew scheduling. Taking the perspective of airports, keywords in this context are runway scheduling, gate assignment and check-in procedures. However, push-back has received little attention by researchers so far. To the best of my knowledge, there is no literature addressing the planning and scheduling of push-back activities explicitly.

2.1.1 Literature on push-back

Several papers address the forecasting of ready-to-push-back-times, among others Schlegel [58], Carr et al. [17], Andersson et al. [4]. Schlegel [58] breaks down the ground handling process into de-boarding, cleaning, catering, fueling, boarding, loading and push-back. A simulation model evaluates the impact of changes in one or more sub-processes. The author proposes a forecasting model that predicts the ready-to-push-back-times during any step of the ground handling process. The model takes into account the current status of the system. The author points out the importance of efficient and on time ground handling processes for airports and airlines. Both contribute to profit maximization and smooth operations. Carr et al. [17] analyze the performance of push-back time forecasting techniques. The authors point out that a high quality forecast may improve the performance of decision support tools for airport surface traffic and thus reduce delays. However, Carr et al. [17] conclude that the stochastic nature of turnaround operations complicates precise forecasts.

The majority of push-back related literature refers to ready-to-push-back-time as an input parameter to gate assignment, taxiway optimization and runway scheduling. Cheng [19] presents a simulation study on the ground movement of aircraft at the gate during push-back. The simulation identifies push-back conflicts which might occur when two planes at neighboring gates enter or exit at the same time and block each other on the taxiway. The author demonstrates that assessing gate assignment decisions with the simulation reduces delays and increases gate utilization. Atkin et al. [5] present models for take-off sequencing, one of which includes a push-back time allocation subproblem, which is solved after the take-off sequence has been set. The basic idea is to determine the take-off sequence first, then calculate the push-back time using forecasts on push-back duration and taxi time. The main goal is to avoid congestion or re-sequencing at the holding area, i.e. to absorb delays at the gate and thus reducing fuel consumption. A simulation experiment shows that delay reductions of 20% or more are possible. In a more recent paper Atkin et al. [6] calculate push-back times after predicting departure delays. Balakrishnan and Jung [9], Keith and Richards [41], Lee et al. [45] and Roling and Visser [57] are other examples addressing the idea of gate holding or push-back control that is giving push-back permission using up-to-date information on taxiway traffic and runway schedules.

2.1.2 Literature on vehicle routing problem

In contrast to the sparse push-back literature there exists a wide range of VRP literature. Since Dantzig and Ramser [22] introduced the Truck Dispatching Problem more than 60 years ago, a great number of VRP papers have emerged. A comprehensive overview of the development of modeling and solving different variants of VRP is given in Golden et al. [35], Laporte [44] and Toth and Vigo [60]. Bektas [12] focuses on the mTSP and provides a literature review on integer programming formulations and solution procedures. The author notes that thus far the mTSP has not received as much attention as the TSP or VRP. Desrochers et al. [26] and Eksioglu et al. [31] introduce a classification scheme for VRP. Desrochers et al. [26] classify VRP according to the four main dimensions of addresses (customers), vehicles, problem characteristics and objective. Addresses can further be specified by, e.g. the number of depots or scheduling constraints. Subcategories of vehicles are for instance the number of vehicles or route duration constraints. Problem characteristics contain type of network and address-to-address restrictions to name a few. The authors state that most models in the literature can be categorized according to their classification.

Despite the large number of VRP papers, the number of papers which address the problem with of a mixed fleet mTSP with time windows, multiple trips and multiple depots is very limited. Nevertheless, literature can be found on single aspects of the introduced problem, e.g. considering either time windows or multiple depots only. I will refer to literature reviews for each aspect and point out some rich VRP papers with the most similarities to my work.

Baldacci et al. [10] give an overview of formulations and solution procedures for the VRP with time window (VRPTW). The authors conclude that column generation based algorithms succeed in solving problems with more than 100 jobs. Golden et al. [35] provide a literature review on heterogeneous fleet VRP (HVRP), also called mixed fleet VRP. They classify variants of HVRP in the literature and compare solution algorithms. The authors observe that no exact algorithm has been introduced for HVRPs so far. Multiple depot VRP (MDVRP) literature is reviewed in Liu et al. [46]. The authors classify the papers by problem variant, model formulation and solution method. The following categories for MDVRP are used: with stochastic demand, mixed fleet, period, backhauling, pickups and deliveries, with time window, with time window and mixed fleet, inter-depot routes and multi objective. They describe nine variants of MDVRP and thereby cover nearly all contributions in this area. So far, researchers have neglected the multiple trip VRP (MTVRP), although this problem variant is of high relevance in practice (see Mingozzi et al. [49]). Multiple trips are needed whenever the number of vehicles is limited. Azi et al. [7] propose an exact algorithm for a single vehicle VRP with time windows and multiple trips. In a subsequent work, the authors extend the problem to multiple vehicles and use a column generation approach (see Azi et al. [8]). Azi et al. [8] are the first to use an exact algorithm to solve a MTVRP with time window. Their algorithm solves all instances with 25 customers and some instances with 50 customers. Macedo et al. [48] also propose an exact algorithm using a pseudo-polynominal network flow model for the MTVRP with time windows, which solves more instances in less time compared to other approaches.

Recent papers combining several generalization aspects and, thus, being most similar to my problem variant are Dondo and Cerda [28], Norin et al. [52], Rieck and Zimmermann [56],Cornillier et al. [20] and Kuhn and Loth [43]. Dondo and Cerda [28] deal with a mixed fleet, multiple depot VRPTW and describe a three-phase heuristic solution approach. In phase I a set of cost efficient feasible clusters is defined. Phase II assigns vehicles to clusters and phase III schedules the tour for one vehicle within one cluster. This so-called cluster-based hierarchical hybrid approach solves problem instances with 100 nodes, 2 depots and a heterogeneous fleet of 10 vehicles within 38 minutes. Norin et al. [52] propose an integrated simulation and optimization approach to improve ground handling processes at airports. The authors investigate the de-icing process. A MIP to schedule de-icing trucks to de-icing jobs is introduced. This MIP is solved with a greedy randomized adaptive search procedures GRASP. Their model include a point of time to deliver the service and the vehicles need to return to the depot to refill de-icing fluid, thus allowing multiple trips. The de-icing model is embedded in an airport operations simulation. The simulation proves superiority of the optimized de-icing schedule over the schedule generated with simple priority rules. The authors present results for a single operating day. Best results regarding delays can be achieved by considering the total airport performance instead of optimizing from the perspective of the de-icing company.

Rieck and Zimmermann [56] present a mixed fleet, multiple trips VRPTW with simultaneous delivery and pick-up. Additionally, a docking bay at the depot for loading and unloading is considered. A time slot for each departing and arriving vehicle at the docking bay must be assigned. The authors test the model with instances up to 30 customers using CPLEX requiring up to 22 minutes runtime.

Cornillier et al. [20] provide a heuristic for the petrol station replenishment problem. Similar to the towing problem, they consider time windows, a heterogeneous fleet, multiple trips and multiple depots. Cornillier et al. [20] describe a procedure to generate a set of feasible trips and a model which finds a solution using this set of restricted trips. The heuristic is capable of solving instances with 50 customers, 10 vehicles and up to 6 depots in 47 - 58 minutes on average. A main difference to this work is the handling of multiple depots. Cornillier et al. [20] assign the vehicles at the beginning of the day to one home depot. During the day the vehicles can only return to the home depot during specified time windows. Contrary, in this work vehicles can return to any depot at any time. Moreover, the fleet heterogeneity is defined differently. Vehicles differ by capacity Cornillier et al. [20], while the vehicles in this work differ by variable costs and technical compatibility.

Kuhn and Loth [43] deal with the scheduling of airport service vehicles which comprise among other vehicles, passenger buses, luggage trailers and fuel trucks. The authors formulate a MIP model and apply an exact solution method as well as a genetic algorithm. They solve real-world scheduling problems at Hamburg Airport involving 17 planes requiring service by 6 service vehicles. Thereby, they demonstrate that travel distances as well as delays can be reduced by at least 20% compared to the manual approach. However, their model does not take into account all specifications of push-back processes. For instance, mixed fleet or multiple trips are not considered.

Overall, there is no literature addressing the scheduling of push-back services. The paper of Kuhn and Loth [43] is most similar to the towing problem. However, their model does not consider the specific characteristics of push-back processes. By combining time windows, mixed fleet, multiple depots and multiple trips in one model, this work contributes to the few existing VRP papers in this area.

2.2 Mathematical model

The model considers a set of planes $\mathcal{P}$, each one requiring a towing job. Each towing job $i \in \mathcal{P}$ is characterized by the plane type, a time window to start the service, set by the earliest time ET_i and the latest time LT_i, a service duration SD_i and a pick up and target location. Each job must be carried out. The service provider faces delay costs DC per time unit if the time window is violated. The maximum aspired delay per job is set to $D^{\max}$, which reflects the service level agreement between the towings service provider and the airlines.

To carry out the jobs, there is a set of heterogeneous vehicles $\mathcal{V}$ (towing tractors). Vehicle $v \in \mathcal{V}$ is characterized by the variable costs VC_v per operating time unit. The compatibility with plane type i is given by $CP_{v,i}$, i.e. tractor v is compatible with job i if $CP_{v,i} = 1$, 0 otherwise.

Moreover, multiple depots of which at least one is a central depot are taken into account. At the start and the end of each planning horizon tractors must depart from and return to (one of) the central depot(s). During the day the tractors (and their drivers) can return to any depot to take a rest. Leaving and returning to a depot is defined as one trip. In contrast to classical VRP the model permits multiple trips per vehicle. The maximum time per trip is set to $T^{\max}$, i.e. each driver must return by the latest every $T^{\max}$ time units to a depot for a rest. The travel time $TT_{v,i,j}$ reflects the time vehicle $v \in \mathcal{V}$ travels from plane $i \in \mathcal{P}$ to plane $j \in \mathcal{P}$. The travel time matrix is obtained by pre-processing information on pick-up and target location of job $i, j \in \mathcal{P}$, taking into account the necessity of changing the towbar between job $i \in \mathcal{P}$ and job $j \in \mathcal{P}$.

In the following, I present two models, which assign tractors to towing jobs while minimizing variable costs. The models are two variants of reflecting multiple trips in the formulation.

2.2.1 Depot model

In the depot model, multiple trips are reflected by determining the number of trips NT per vehicle and adding virtual depots for each trip. Figure 2.1 shows an example for a problem with two real depots with depot 1 as central depot and three trips (the rows refer to the depots and each trip is represented by a gray box in the figure). The number of depot nodes in this example is ten (S1 to S5 and E1 to E5). For each trip one depot is represented by one starting depot node (tractor leaves the depot) and one ending depot node (tractor returns to the depot). With two depots, there are four nodes per trip. With three trips there are in total twelve nodes. However, since the first trip must start and the last trip must end in the central depot, starting depot 2 of the first trip and ending depot 2 of the last trip can be discarded. This results in ten depot nodes.

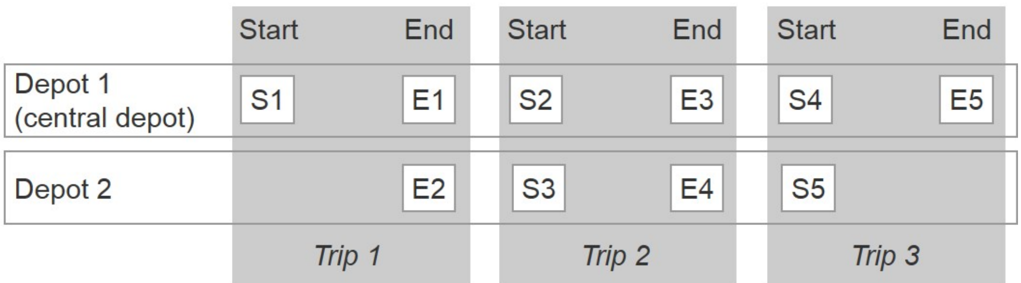

Figure 2.1: Depot structure (example)

$\mathcal{S}$ denotes the set of starting depot nodes and $\mathcal{E}$ the set of ending depot nodes. The number of trips depends on the length of the planning horizon, the maximum time per trip, the number of jobs and the number of tractors. Allowing more trips than required does not impact the optimal objective function value, but increases the runtime. Since returning to the depot typically means extra time and costs, the model minimizes the number of trips per vehicle. Previous computational test have shown that, as a rule of thumb, dividing the length of the planning horizon by the maximum time per trip $T^{\max}$ and adding 1-2 “buffer trip” usually is a reasonable value.

A possible solution is shown in Figure 2.2. Ten planes represented by nodes P1 to P10 require a towing job. There are two tractors: tractor A and B. Each one can perform a maximum of three trips. Between each trip the tractor can return to either one of the two depots, with depot 1 being the central depot. In this example, tractor A leaves the central depot S1 to serve P2, P1, P6 and returns to depot 2 (E2). Consequently, its second trip

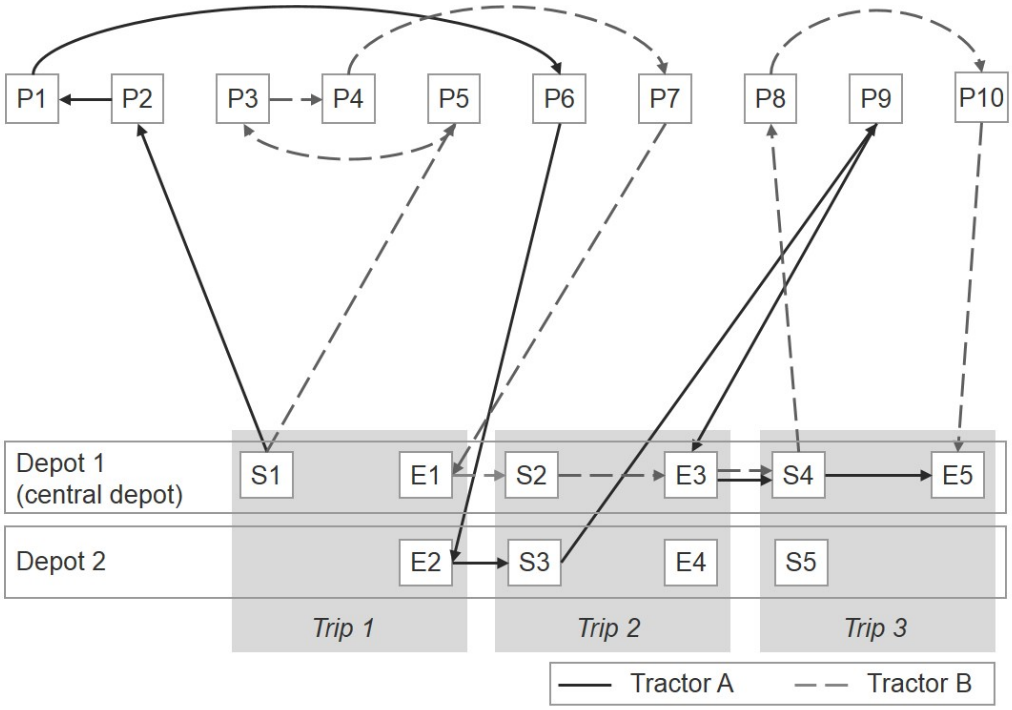

Figure 2.2: Output of depot model (example)

starts in depot 2 (S3), and after serving P9 the tractor returns to depot 1 (E5). The third trip is an empty trip, i.e. tractor A remains in the central depot. To connect the trips of a vehicle $v \in \mathcal{V}$, the travel time from an ending depot node to the starting depot node of the following trip is set to 0. An example of a travel time matrix for the depot model is given in Figure 2.3. Each column and line represent a node, the figure shows the travel time from one node (row) to another (column). The travel time matrix contains following preprocessed information and assumptions:

Forbidden routes. The travel time between forbidden routes is set to infinity. This includes

- routes from plane $i \in \mathcal{P}$ to the same plane i,
- routes from plane $i \in \mathcal{P}$ to starting depot node $j \in \mathcal{S}$,
- routes from ending depot node $i \in \mathcal{E}$ to plane $j \in \mathcal{P}$,
- routes between starting depot nodes $i, j \in \mathcal{S}$ and
- routes between ending depot node $i, j \in \mathcal{E}$.

Decision variables related to arcs with a value of infinity (infeasible routes) are set to 0 in the model implementation.

To / From	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	S1	S2	S3	S4	S5	E1	E2	E3	E4	E5
P1	∞	6	1	8	7	4	8	8	8	6	∞	∞	∞	∞	∞	4	2	4	2	4
P2	8	∞	8	8	7	5	8	8	8	6	∞	∞	∞	∞	∞	5	3	5	3	5
P3	1	6	∞	8	7	3	8	8	7	6	∞	∞	∞	∞	∞	3	2	3	2	3
P4	8	6	8	∞	7	5	8	1	8	6	∞	∞	∞	∞	∞	2	3	2	3	2
P5	9	7	9	9	∞	6	9	9	9	7	∞	∞	∞	∞	∞	6	4	6	4	6
P6	4	5	3	7	6	∞	7	7	7	5	∞	∞	∞	∞	∞	7	2	7	2	7
P7	8	6	8	8	7	5	∞	8	2	6	∞	∞	∞	∞	∞	5	3	5	3	5
P8	8	6	8	1	7	5	8	∞	8	6	∞	∞	∞	∞	∞	5	3	5	3	5
P9	8	9	8	9	10	8	9	9	∞	9	∞	∞	∞	∞	∞	6	7	6	7	6
P10	8	9	8	9	10	8	9	9	10	∞	∞	∞	∞	∞	∞	5	7	5	7	5
S1	4	5	4	5	6	4	5	5	6	5	∞	∞	∞	∞	∞	0	∞	∞	∞	∞
S2	4	5	4	5	6	4	5	5	6	5	∞	∞	∞	∞	∞	∞	∞	0	∞	∞
S3	2	3	2	3	4	2	3	3	4	2	∞	∞	∞	∞	∞	∞	∞	∞	0	∞
S4	4	5	4	5	6	4	5	5	6	5	∞	∞	∞	∞	∞	∞	∞	∞	∞	0
S5	2	3	2	3	4	2	3	3	4	2	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞
E1	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	0	∞	∞	∞	∞	∞	∞	∞	∞
E2	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	0	∞	∞	∞	∞	∞	∞	∞
E3	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	0	∞	∞	∞	∞	∞	∞
E4	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	0	∞	∞	∞	∞	∞
E5	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞

Figure 2.3: Travel time matrix (example for depot model)

Empty trips. Tractors can stay in the depot (empty trip). In the model, the tractor drives from the starting node directly to the ending node. Therefore, the travel time from the starting depot node to the ending depot node of the same trip is set to 0 if both nodes represent the same depot. These cases are marked in black in Figure 2.3. For instance, the travel time from $S1$ to $E1$ is set to 0 since $S1$ and $E1$ represent both depot 1 of the trip 1.

Connection between trips. To connect the trips of vehicle $v \in \mathcal{V}$, the travel time from an ending depot node to the starting depot node of the following trip is set to 0 (marked dark gray in Figure 2.3). For instance, the travel time from $E1$ to $S2$ is 0, since both $E1$ and $S2$ represent the same depot (depot 1) and $E1$ is the ending depot node for the first trip, while $S2$ is the starting depot node for the second trip.

Change of towbars. The travel time in the matrix already includes the additional time to return to the depot to change the towbar. Changing the towbar at the depot is not considered as returning to the depot. In other words, a tractor returning to the depot in order to change the towbar only, does not end a trip. Furthermore, returning to the depot to take a rest already includes the time to change the towbar before starting the new trip after the break.

Pick-up and target location. Maintenance towing and repositioning have different pick-up and target locations. This results in an asymmetric travel time matrix. For instance, the time to drive from job $P1$ to job $P2$ is 6 time units, while it takes 8 time units the other way round.

The following notation to formulate the depot model is used:

Sets:

$\mathcal{P}$	Set of planes requiring towing
$\mathcal{S}_r$	Set of depots where the r-th trip can be started, with $\mathcal{S} = \mathcal{S}_1 \cup \mathcal{S}_2 \cup ... \cup \mathcal{S}_{R^{max}}$
$\mathcal{E}_r$	Set of depots where the r-th trip can be ended, with $\mathcal{E} = \mathcal{E}_1 \cup \mathcal{E}_2 \cup ... \cup \mathcal{E}_{R^{max}}$
$\mathcal{N}$	Set of all nodes with $\mathcal{N} = \{\mathcal{P} \cup \mathcal{S} \cup \mathcal{E}\}$
$\mathcal{V}$	Set of vehicles

Parameters:

VC_v	Variable costs of vehicle v per operating time unit
DC	Delay costs per time unit
$TT_{v,i,j}$	Travel time of tractor v to drive from node i to node j
SD_i	Service duration to serve plane i or resting time at ending depot node i
$CP_{v,i}$	1, if tractor v is compatible with plane i, 0 otherwise
ET_i	Earliest time to start service at node i
LT_i	Latest time to start service at node i
$D^{\max}$	Maximum delay per job
$T^{\max}$	Maximum duration of one trip
$R^{\max}$	Number of trips per vehicle
$M_{v,i,j}$	Parameter specific big M with $(M_{v,i,j} \geq LT_i + D_{\max} + SD_i + TT_{v,i,j} - ET_j)$

Functions:

$SD(i)$	Maps ending depot i to each potential starting depot of the same trip
$ED(i)$	Maps starting depot i to the ending depot of the directly preceding trip

Variables:

$x_{v,i,j}$	1, if tractor v visits node j immediately after having visited node i, 0 otherwise
$b_{v,i}$	Beginning time of tractor v to serve node i
d_i	Delay of service at plane i (compared to LT_i)

$$\text{Minimize} \sum_{v \in \mathcal{V}} VC_v \cdot \Big(\sum_{i,j \in \mathcal{N}} TT_{v,i,j} \cdot x_{v,i,j} + \sum_{i \in \mathcal{P}} \sum_{j \in \mathcal{N}} SD_i \cdot x_{v,i,j} \Big) + DC \cdot \sum_{i \in \mathcal{P}} d_i \tag{1a}$$

subject to

$$\sum_{v \in \mathcal{V}} \sum_{j \in \mathcal{P} \cup \mathcal{E}} CP_{v,i} \cdot x_{v,i,j} = 1 \qquad \forall i \in \mathcal{P} \tag{1b}$$

$$\sum_{i \in \mathcal{S}_r} \sum_{j \in \mathcal{P} \cup \mathcal{E}_r} x_{v,i,j} = 1 \qquad \forall v \in \mathcal{V}, r \in \{1, \ldots, R^{\max}\} \tag{1c}$$

$$\sum_{i \in \mathcal{N}} x_{v,i,h} - \sum_{j \in \mathcal{N}} x_{v,h,j} = 0 \qquad \forall v \in \mathcal{V},\ h \in \mathcal{N} \setminus \{\mathcal{S}_1 \cup \mathcal{E}_{R^{max}}\} \tag{1d}$$

$$ET_i \cdot \sum_{j \in \mathcal{N}} x_{v,i,j} \leq b_{v,i} \qquad \forall v \in \mathcal{V},\ i \in \mathcal{P} \tag{1e}$$

$$b_{v,i} + SD_i + TT_{v,i,j} \leq b_{v,j} + M_{v,i,j} \cdot (1 - x_{v,i,j}) \qquad \forall v \in \mathcal{V},\ i,j \in \mathcal{N} \tag{1f}$$

$$\sum_{v \in \mathcal{V}} b_{v,i} - LT_i \leq d_i \qquad \forall i \in \mathcal{P} \tag{1g}$$

$$b_{v,i} - b_{v,\tilde{i}} \leq T^{\max}, \qquad \forall v \in \mathcal{V},\ i \in \mathcal{E}, \tilde{i} \in SD(i) \tag{1h}$$

$$b_{v,ED(i)} \leq b_{v,i} \qquad \forall v \in \mathcal{V},\ i \in \mathcal{S} \setminus \{\mathcal{S}_1\} \tag{1i}$$

$$x_{v,i,j} \in \{0,1\} \qquad \forall v \in \mathcal{V},\ i,j \in \mathcal{N} \tag{1j}$$

$$b_{v,i} \geq 0 \qquad \forall v \in \mathcal{V},\ i \in \mathcal{N} \tag{1k}$$

$$0 \leq d_i \leq D^{\max} \qquad \forall i \in \mathcal{P} \tag{1l}$$

The objective function (1a) minimizes the variable costs which arise for the tractor operation time (driving and service time) and the penalty costs due to delays. The model takes an operational perspective for which the fleet is given and therefore depreciation costs of the tractors are not taken into account. Demand constraints (1b) ensure that each plane i is served by exactly one compatible vehicle v.

Constraints (1c) force each tractor to start a trip r in one of the starting depots $\mathcal{S}_r$. The travel time matrix ensures the connection between trips.

Taking the example shown in Figure 2.2, the first and second trips are connected by setting the travel time from $E1$ to $S2$ and from $E2$ to $S3$ to 0, while all other travel times starting from nodes $E1$ and $E2$ are set to ∞. Therefore, to start the second trip, vehicle v has to return to either $E1$ or $E2$ at the end of the first trip. Flow balance constraints (1d) force vehicle v to depart from node h if it has entered in node h.

Constraints (1e) ensure that the start time of tractor v to serve plane i is not earlier than ET_i. Constraints (1f) consider time consistency: If tractor v serves plane i first and plane j next, the service at plane j cannot start before tractor v has finished service at plane i and driven from plane i to plane j. Constraints (1g) define the delay at plane i. Since d_i is non-negative the delay is zero if the start time $b_{v,i}$ is earlier than LT_i, otherwise the delay is the difference between the start time and the latest possible start time, i.e. $b_{v,i} - LT_i$.

Constraints (1h) ensure each trip duration (time between leaving and returning to the depot) not to exceed the maximum trip duration $T^{\max}$. $SD(i)$ is a function that maps each ending depot i to each potential starting depot of the same trip. Looking at the example in Figure 2.1, it maps E1 to S1, E2 to S1, E3 to S2, E3 to S3, E4 to S2, E4 to S3, E5 to S4 and E5 to S5. Constraints (1i) ensure that the next trip can only start after the previous trip has ended. Here, $ED(i)$ is a function that maps each starting depot i to the ending depot of the directly preceding trip, i.e. in Figure 2.1 S2 to E1, S3 to E2, S4 to E3 and S5 to E4.

Variable definitions are given in (1j)-(1l). $D^{\max}$ reflects the service aspiration level of the service provider. However, if no feasible solution exists given this restriction, $D^{\max}$ needs to be increased in the model.

2.2.2 Tractor model

In contrast to the depot model, not depots but tractors are duplicated to reflect multiple trips. In this model, one tractor is represented by several virtual tractors. Each virtual tractor can accomplish one trip, by stringing together the trips of all virtual tractors representing the same actual tractor, a feasible tour is generated for this tractor. Figure 2.4 shows the result of the tractor model. In this example, three trips are permitted and there are two actual tractors available. For each additional trip, the set of actual tractors is duplicated, resulting in six tractors in total. Tractors A1, A2 and A3 represent one actual tractor. A2 refers to the second trip of tractor

A. Both Figure 2.2 and Figure 2.4 are representations of the same result.

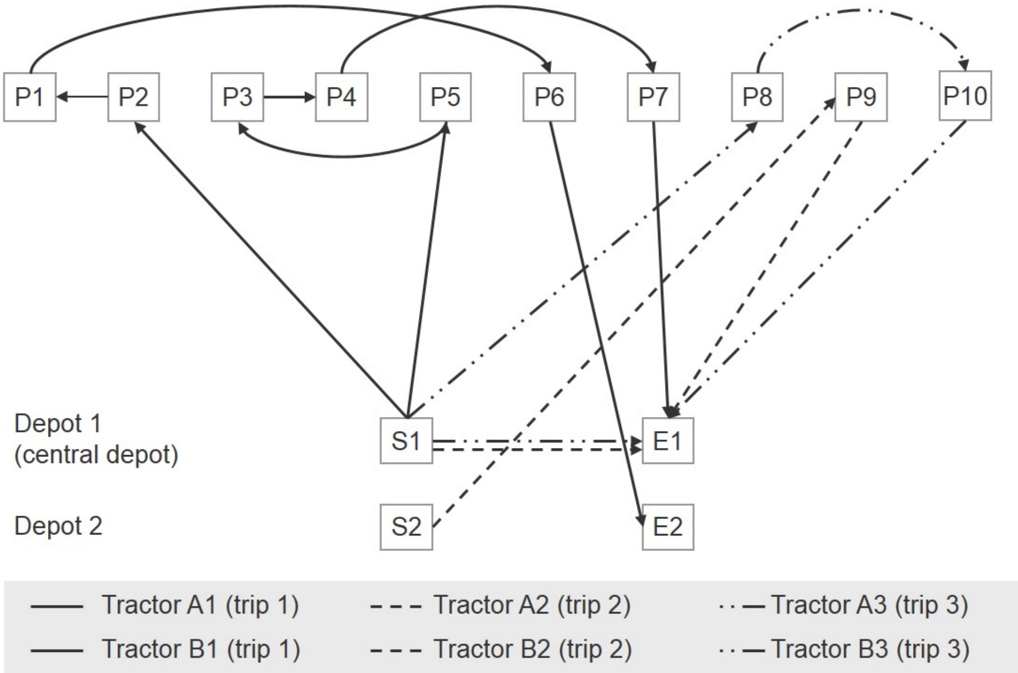

Figure 2.4: Output of tractor model (example)

The following notation is used to formulate the tractor model:

Sets:

$\mathcal{P}$	Set of planes requiring towing
$\mathcal{S}$	Set of depots to start a trip with $\mathcal{S} = \{s_1, ..., s_W\}$, s_1 as central depot
$\mathcal{E}$	Set of depots to end a trip with $\mathcal{E} = \{e_1, ..e_W\}$, e_1 as central depot
$\mathcal{N}$	Set of all nodes with $\mathcal{N} = \{\mathcal{P} \cup \mathcal{S} \cup \mathcal{E}\}$
$\mathcal{V}$	Set of vehicles (tractors), with $\mathcal{V} = \{\mathcal{V}_1 \cup, ..., \cup \mathcal{V}_R\}$
$\mathcal{V}_r$	Set of vehicles for r-th trip

Parameters:

Z	Number of actual vehicles with $Z =\mid \mathcal{V}_r \mid$
VC_v	Variable cost of tractor per operating time unit
DC	Delay cost per time unit
$TT_{v,i,j}$	Travel time of tractor v to drive from plane i to plane j

SD_i	Service duration to serve plane i or resting time at ending depot node i
$CP_{v,i}$	1, if tractor v is compatible with plane i, 0 otherwise
ET_i	Earliest time to start service at node i
LT_i	Latest time to start service at node i
$D^{\max}$	Maximum delay per job
T^{max}	Maximum duration of one trip (time between leaving and returning to a depot)
$M_{v,i,j}$	Parameter specific big M with $(M_{v,i,j} \geq LT_i + D_{\max} + SD_i + TT_{v,i,j} - ET_j)$
Functions:	
$f(e)$	Maps ending depot to starting depot of same depot w (e.g. $f(e_1) = s_1,\ f(e_2) = s_2$)
Variables:	
$x_{v,i,j}$	1, if tractor v visits node j immediately after having visited node i, 0 otherwise
$b_{v,i}$	beginning time of tractor v to serve node i
d_i	delay of service at plane i (compared to LT_i)

$$\text{Minimize} \sum_{v\in\mathcal{V}} \sum_{i,j\in\mathcal{N}} VC_v \cdot TT_{v,i,j} \cdot x_{v,i,j} + \sum_{v\in\mathcal{V}} \sum_{i\in\mathcal{P}} \sum_{j\in\mathcal{N}} VC_v \cdot SD_i \cdot x_{v,i,j} + DC \cdot \sum_{i\in\mathcal{P}} d_i \tag{2a}$$

subject to

$$\sum_{v\in\mathcal{V}} \sum_{j\in\mathcal{P}\cup\mathcal{E}} CP_{v,i} \cdot x_{v,i,j} = 1 \qquad \forall i \in \mathcal{P} \tag{2b}$$

$$\sum_{j\in\mathcal{P}\cup\mathcal{E}} x_{v,s_1,j} = 1 \qquad \forall v \in \mathcal{V}_1 \tag{2c}$$

$$\sum_{i\in\mathcal{P}\cup\mathcal{S}} x_{v,i,e_1} = 1 \qquad \forall v \in \mathcal{V}_R \tag{2d}$$

$$\sum_{s\in\mathcal{S}} \sum_{j\in\mathcal{P}\cup\mathcal{E}} x_{v,s,j} = 1 \qquad \forall v \in \mathcal{V}_2, ..., \mathcal{V}_R \tag{2e}$$

$$\sum_{i\in\mathcal{P}\cup\mathcal{S}} \sum_{e\in\mathcal{E}} x_{v,i,e} = 1 \qquad \forall v \in \mathcal{V}_1, ..., \mathcal{V}_{R-1} \tag{2f}$$

$$\sum_{i \in \mathcal{P} \cup \mathcal{S}} x_{v,i,e} - \sum_{j \in \mathcal{P} \cup \mathcal{E}} x_{Z+v,f(e),j} = 0 \qquad \forall v \in \mathcal{V}_1, ..., \mathcal{V}_{R-1},\ e \in \mathcal{E} \tag{2g}$$

$$\sum_{i \in \mathcal{P}} x_{v,i,h} - \sum_{j \in \mathcal{P}} x_{v,h,j} = 0 \qquad \forall v \in \mathcal{V},\ h \in \mathcal{P} \tag{2h}$$

$$b_{v,e} - M_{v,i,j} \cdot \sum_{i \in \mathcal{P} \cup \mathcal{S}} x_{v,i,e} \leq 0 \qquad \forall v \in \mathcal{V},\ e \in \mathcal{E} \tag{2i}$$

$$b_{v,s} - M_{v,i,j} \cdot \sum_{j \in \mathcal{P} \cup \mathcal{E}} x_{v,s,j} \leq 0 \qquad \forall v \in \mathcal{V},\ s \in \mathcal{S} \tag{2j}$$

$$\sum_{e \in \mathcal{E}} b_{v,e} \leq \sum_{s \in \mathcal{S}} b_{Z+v,s} \qquad \forall v \in \mathcal{V}_1, ..., \mathcal{V}_{R-1} \tag{2k}$$

$$ET_i \cdot \sum_{j \in \mathcal{P} \cup \mathcal{E}} x_{v,i,j} \leq b_{v,i} \qquad \forall v \in \mathcal{V},\ i \in \mathcal{P} \tag{2l}$$

$$b_{v,i} + SD_i + TT_{v,i,j} \leq b_{v,j} + M_{v,i,j} \cdot (1 - x_{v,i,j}) \qquad \forall v \in \mathcal{V},\ i, j \in \mathcal{N} \tag{2m}$$

$$\sum_{v \in \mathcal{V}} b_{v,i} - LT_i \leq d_i \qquad \forall i \in \mathcal{P} \tag{2n}$$

$$\sum_{e \in \mathcal{E}} b_{v,e} - \sum_{s \in \mathcal{S}} b_{v,s} \leq T^{max} \qquad \forall v \in \mathcal{V} \tag{2o}$$

$$x_{v,i,j} \in \{0; 1\} \qquad \forall v \in \mathcal{V},\ i, j \in \mathcal{N} \tag{2p}$$

$$b_{v,i} \geq 0 \qquad \forall v \in \mathcal{V},\ i \in \mathcal{N} \tag{2q}$$

$$0 \leq d_i \leq D^{\max} \qquad \forall i \in \mathcal{P} \tag{2r}$$

The objective function (2a) minimizes the variable costs which incur for the tractor operation time (driving and service time) and the penalty costs due to delays. Demand constraints (2b) ensure that each plane i is exactly served by one vehicle v which is compatible with the plane type.

Constraints (2c) and (2e) require each tractor of the first trip V_1 to depart from starting node s_1 (central depot) and each tractor V_r of the r-th trip ($r = 2..R$) to depart from one of the starting depots $\mathcal{S}$. Constraints (2d) and (2f) ensures that each tractor of the last trip V_R ends in Ending Node e_1 (central depot)and that each tractor V_r of trip $r = 1..(R-1)$ ends in one of the ending depots $\mathcal{E}$. Constraints (2g) ensure vehicle $z + v$ to start the direct succeeding trip in the same depot in which vehicle v has ended the previous trip. Tractor v and tractor $z + v$ represent the same tractor. Flow balance constraints (2h) require vehicle v to leave node h, if it has enters node h.

Constraints (2i) and (2j) set all $b_{v,e}$ and $b_{v,s}$ to 0, if the respective depot is not visited by tractor v. Constraints (2k) ensure that a actual same tractor v and $z+v$ can start a new trip only after the previous trip has ended. Constraints (2l) ensure that the starting time of tractor v to serve plane i is not earlier than ET_i. Constraints (2m) ensure, if tractor v serves plane i and directly afterwards plane j, service at plane j cannot start before tractor v has finished service at plane i and drove from plane i to plane j. Constraints (2n) define the delay at plane i. Since d_i is non-negative, the delay is zero if the actual starting time $b_{v,i}$ is earlier than LT_i, otherwise the delay is the difference between the actual starting time and the latest starting time. Constraints (2o) ensure that each trip (time between leaving from and returning to depot) does not exceed the maximum trip duration T^{max}. Variable definitions are given in (2p)-(2r).

Initial computational tests show that the depot model is equivalent or even outperforms the tractor model with regards to solution quality and runtime (see Appendix B). Therefore, the remaining chapter focuses on the depot model formulation.

2.3 Column generation heuristic

The TSP and VRP is NP-hard, adding aspects like multiple depots and trips makes the problem more difficult to solve. Baldacci et al. [10] investigate exact algorithms for solving VRP and conclude that column generation based algorithms handle VRP successfully and provide a lower bound very close to the optimal solution value. Therefore, I propose a column generation based heuristic to solve the scheduling model (1a) - (1l). Desaulniers et al. [24] describe the basic idea of column generation and provide an overview on solution methods and applications. Examples for recent papers applying a column generation approach to solve VRP are Azi et al. [8], Ceselli et al. [18] and Oppen et al. [53].

For column generation the MIP is decomposed into a Master Problem (MP) and one or several Subproblems (SP). Column generation is an iterative procedure that considers a subset of feasible columns (tours) at a time. It generates new columns via one or more separated optimization problem(s), the so-called Subproblem(s), on an as needed basis (see Barnhart et al. [11], Dantzig and Wolfe [23], Vanderbeck and Wolsey [61]), while MP provides a coordination structure. The procedure starts with a subset of columns in the Restricted Master Problem (RMP). Then the linear relaxation of RMP is solved to optimality. In the next step, the dual variable information is used to price out absent columns with the use of SP. If a promising column is identified, it is added to RMP and the RMP relaxation is re-optimized. Otherwise, the procedure terminates with a valid lower bound in case of a minimization problem for the original MIP. In the following, MP is stated using constraints (1b) as a set covering type model. The remaining constraints form the solution space of SP.

Master Problem. The following additional notation is used to formulate MP:

Sets:

$\mathcal{B}$	Set of vehicle types
$\mathcal{A}(b)$	Set of routes associated with vehicle type b

Parameters:

$RC_{b,a}$	Costs of route a associated with vehicle type b
CW	Costs associated with auxiliary variable w_i
$Y_{b,a,i}$	1, if route a associated with type b covers plane i, 0 otherwise
NV_b	Number of vehicles of type b

Variables:

$\lambda_{b,a}$	1, if route a associated with type b is selected, 0 otherwise
w_i	1, if plane i is not served by selected routes, 0 otherwise

$$\text{Minimize} \sum_{b \in \mathcal{B}} \sum_{a \in \mathcal{A}(b)} RC_{b,a} \cdot \lambda_{b,a} + \sum_{i \in \mathcal{P}} CW \cdot w_i \tag{3a}$$

subject to

$$\sum_{b \in \mathcal{B}} \sum_{a \in \mathcal{A}(b)} Y_{b,a,i} \cdot \lambda_{b,a} + w_i \geq 1 \qquad \forall i \in \mathcal{P} \tag{3b}$$

$$\sum_{a \in \mathcal{A}(b)} \lambda_{b,a} \leq NV_b \qquad \forall b \in \mathcal{B} \tag{3c}$$

$$\lambda_{b,a}; w_i \in \{0,1\} \qquad \forall b \in \mathcal{B}, a \in \mathcal{A}(b); i \in \mathcal{P} \tag{3d}$$

The objective function (3a) minimizes the costs associated with selected routes for each tractor type and the penalty costs for not serving planes. The auxiliary variables ensure feasibility in the course of the column generation procedure. They can be seen as unit columns with which RMP is initialized. Such a column covers exactly one flight and has very high costs ($RC_{b,a} \ll$

CW for all $a \in \mathcal{A}(b)$). Constraints (3b) ensure that each plane $i \in \mathcal{P}$ is served. If plane i is not included in any of the selected routes, the auxiliary variable w_i is set to 1 to ensure feasibility. The algorithm starts with no columns. Therefore w_i for all $i \in \mathcal{P}$ are set to 1 in the first iteration. Constraints (3c) ensure for each tractor type that the number of selected routes does not exceed the number of available vehicles of that type. The range for the decision variables are given in (3d).

The dual solution of RMP is obtained from relaxing the integrality condition and solving RMP with a subset of columns. Let $\delta_i \geq 0$ denote the dual values of the demand constraints (3b) and $\mu_b \leq 0$ the dual values of the convexity constraints (3c). In terms of MP notation, the reduced costs of column a associated with tractor type b is

$$\bar{c}_{b,a} = RC_{b,a} - \left(\sum_{i \in \mathcal{P}} \delta_i \cdot Y_{b,a,i} + \mu_b \right) \tag{4}$$

with $RC_{b,a}$ (costs of tour a for vehicle type b) defined as

$$\begin{aligned} RC_{b,a} = & \sum_{i,j \in \mathcal{N}} VC_b \cdot TT_{b,i,j} \cdot X_{b,i,j} + \\ & \sum_{i \in \mathcal{P}} \sum_{j \in \mathcal{N}} VC_b \cdot SD_i \cdot X_{b,i,j} + DC \cdot \sum_{i \in \mathcal{P}} D_{b,i}. \end{aligned} \tag{5}$$

Here, VC_b denotes the variable costs and TT_b the travel time matrix of tractor type b. $X_{b,i,j}$ and $D_{b,i}$ represent the values of the decision variables in SP. To verify LP optimality of RMP, $\bar{c}_a \geq 0$ has to hold for all absent columns $a \notin \mathcal{A}(b)$ and any tractor type $b \in \mathcal{B}$. For each tractor type b one SP is created. Index a in (4) dropped to derive the objective function for SP(b). The new binary variable $y_{b,i}$ replaces the parameter $Y_{b,a,i}$ with

$$y_{b,i} = \begin{cases} 1, & \text{if plane } i \in \mathcal{P} \text{ is served by tractor } b \\ 0, & \text{otherwise.} \end{cases}$$

Whenever a new column is found with negative reduced costs (i.e. the objective value of SP is negative), the column is added to RMP and a new iteration starts. The procedure terminates as soon as no further column with negative reduced costs exists.

Subproblem (b). The formulation of SP(b) looks as follows:

$$\text{Minimize} \sum_{i,j\in\mathcal{N}} VC_b \cdot TT_{b,i,j} \cdot x_{i,j} + \sum_{i\in\mathcal{P}}\sum_{j\in\mathcal{N}} VC_b \cdot SD_i \cdot x_{i,j} \tag{6a}$$
$$+ DC \cdot \sum_{i\in\mathcal{P}} d_i - \left(\sum_{i\in\mathcal{P}} \delta_i \cdot y_{b,i} + \mu_b\right)$$

subject to

$$\sum_{j\in\mathcal{N}} x_{i,j} - y_{b,i} = 0 \qquad \forall i \in \mathcal{P} \tag{6b}$$
$$CP_{b,i} \leq y_{b,i} \qquad \forall i \in \mathcal{P} \tag{6c}$$
$$\sum_{i\in\mathcal{S}_r}\sum_{j\in\mathcal{P}\cup\mathcal{E}_r} x_{i,j} = 1 \qquad \forall r \in \{1,\ldots,R^{max}\} \tag{6d}$$
$$\sum_{i\in\mathcal{N}} x_{i,h} - \sum_{j\in\mathcal{N}} x_{h,j} = 0 \qquad \forall h \in \mathcal{N} \setminus \{\mathcal{S}_1 \cup \mathcal{E}_{R^{max}}\} \tag{6e}$$
$$ET_i \cdot \sum_{j\in\mathcal{N}} x_{i,j} \leq b_i \qquad \forall i \in \mathcal{P} \tag{6f}$$
$$b_i + SD_i + TT_{b,i,j} \leq b_j + M_{i,j} \cdot (1 - x_{i,j}) \qquad \forall i,j \in \mathcal{N} \tag{6g}$$
$$b_i - LT_i \leq d_i \qquad \forall i \in \mathcal{P} \tag{6h}$$
$$b_i - b_{\tilde{i}} \leq T^{max}, \qquad \forall i \in \mathcal{E}, \tilde{i} \in SD(i) \tag{6i}$$
$$b_{ED(i)} \leq b_i \qquad \forall i \in \mathcal{S} \setminus \{\mathcal{S}_1\} \tag{6j}$$
$$x_{i,j} \in \{0,1\}\,,\ b_i \geq 0 \qquad \forall i,j \in \mathcal{N} \tag{6k}$$
$$y_{b,i} \in \{0,1\}\,,\ 0 \leq d_i \leq D^{\max} \qquad \forall i \in \mathcal{P} \tag{6l}$$

The objective function (6a) minimizes the reduced costs of a new potential column to be added to RMP. Thereby the improvement of the objective function in RMP over the current iteration is maximized. The constraints (6d)-(6j) are equivalent to the constraints (1c)-(1i). Constraints (6b) link the x variable to the y variable. Constraints (6c) ensure the compatibility of vehicles type b with plane type $i \in \mathcal{P}$. Finally, constraints (6k) and (6l) define the decision variables.

A new tour is given by the solution of SP(b). Particularly, the new column a associated with tractor type b is given as

$$\begin{bmatrix} RC_{b,a} \\ \overrightarrow{Y}_{b,a} \\ \mathbf{1}_b \end{bmatrix}$$

where $RC_{b,a}$ is defined by (5), $\overrightarrow{Y}_{b,a}$ is a vector with $|\mathcal{P}|$ elements with $Y_{b,a,i} = y_{b,i}$ for all $i \in \mathcal{P}$ and $\mathbf{1}_b$ is a unit vector with length $|\mathcal{B}|$ where at position b is 1 and else 0. After solving the LP-relaxation of RMP, the existing columns are used to find a feasible solution. In other words, RMP is solved as IP.

2.4 Computational study

In this section I investigate the performance of the column generation heuristic (CGH). The computational tests serve to determine the manageable problem size for the case study in Chapter 2.5. All computations are performed on a 3.3 GHz PC (Intel(R) Core(TM) i3-2120 CPU) with 4 GB RAM running under Windows 7 operating system. I use IBM ILOG CPLEX Optimization Studio 12.2 in its default settings to code and solve the model in the compact formulation (in the following referred to as MIP). CGH is implemented in IBM ILOG CPLEX Optimization Studio 12.2, extended by some java methods. No runtime limit is set for the tests.

The CGH procedure starts with zero real columns in RMP. Initial tests showed that solving SP in the first few iteration not to optimality positively impacts the runtime. Therefore, the CGH procedure does not solve SP optimally in the first 50 iterations for problem instances with 10 or 25 planes and in the first 100 iterations for problem instances with 50 planes. Instead, the first feasible solution with negative reduced costs of SP is added as a new column to RMP. Thus, the time per iteration decreases while the total number of required iterations increases. The test design is described in the following. I examine problem instances with

- a heterogeneous fleet of 15 tractors (10 of type A and 5 of type B),
- 10, 25 and 50 planes,
- 1 and 2 depots, with depot 1 as the central depot and
- 1, 2 and 3 trips.

All possible combinations of the parameter settings described above result theoretically in 18 problem instances in total. However, instances with one trip cannot be combined with multiple depots since each route has to start and end at the central depot. This results in 15 instances. For a homogenous fleet of 15 tractors I investigate problem instances with 10 planes, 1 or 2 depots and 1, 2 or 3 trips yielding in 5 additional instances. Again one trip cannot be combined with multiple depots. Thus, there are in in total 20 problem instances. Table 2.1, Table 2.2 and Table 2.3 provide an overview of the test results.

Prob	# Pln	# Dpt	# Trp	T^{max}	# Trctr	MIP IP Val	MIP Gap* %	MIP LP Relax	MIP Time Sec	CGH IP Val	CGH Gap* %	CGH LP Relax	CGH Time Sec	CGH SP Sec
1	10	1	1	60	10/5	237	0.0	180.0	1	237	0.0	237.0	1	1
2	10	1	2	60	10/5	225	0.0	178.0	10	225	0.0	225.0	1	1
3	10	1	3	60	10/5	225	0.0	178.0	10	225	0.0	225.0	2	1
4	10	2	2	60	10/5	212	0.0	177.0	122	212	0.0	212.0	1	1
5	10	2	3	60	10/5	212	0.0	177.0	4,012	212	0.0	212.0	4	4

*Gap=(IP Value - LP Relax) / IP Value · 100

Table 2.1: Computational test results - Heterogeneous fleet, 10 planes

Each line in the tables represents one problem instance. The problem number is given in the first column. Columns 2 to 6 describe the problem instance by stating the number of planes (# Pln), the number of depots (# Dpt), the number of trips (# Trp), the maximum time per trip (T^{max}) and the number of tractors (# Trctr). The next four columns display the results of compact MIP (1a) - (1l). The objective function value of the IP, the optimality gap, the value of the LP relaxation and the total runtime are given. Columns 11 to 14 show the results for the CGH. Additionally, the runtime of the SP for the CGH is stated in the last column.

The variable costs VC per minute are set to 2 Euro for vehicle type A (towless tractor) and 1 Euro for vehicle type B (towbar tractor). The delay costs DC are set to 79 Euro for each minute of delay. For confidentiality reasons these are not the actual costs. However, the ratio between the various costs corresponds to the real-life data.

Comparing the results of problem instance 1 to 5 with a heterogeneous fleet and 10 planes (see Table 2.1), the following conclusions can be drawn:

- The runtime of the MIP increases significantly with increasing number of depots and trips. While the runtime to solve problem instance 1 (1 depot,

Prob	# Pln	# Dpt	# Trp	T^{max}	# Trctr	MIP IP Val	MIP Gap* %	MIP LP Relax	MIP Time Sec	CGH IP Val	CGH Gap* %	CGH LP Relax	CGH Time Sec	CGH SP Sec
6	10	1	1	60	15	167	0.0	137.0	1	167	0.0	167.0	2	1
7	10	1	2	60	15	167	0.0	130.0	29	167	0.0	167.0	1	1
8	10	1	3	60	15	167	0.0	130.0	1,121	167	0.0	167.0	2	1
9	10	2	2	60	15	158	0.0	129.0	1,634	158	0.0	158.0	2	1
10	10	2	3	60	15	158	0.0	129.0	611,012	158	0.0	158.0	5	3

*Gap=(IP Value - LP Relax) / IP Value · 100

Table 2.2: Computational test results - Homogeneous fleet, 10 planes

1 trip) is just 1 second, a runtime of 10 seconds is required for problem instance 2 (1 depot, 2 trips). Also, adding a depot impacts the runtime. This can be observed when comparing instance 2 with 4 (10 seconds vs. 122 seconds) or instance 3 with 5 (10 seconds vs. 67 minutes).

- CGH provides a tighter lower bound than MIP. While the lower bound provided by CGH equals the optimal solution, CPLEX calculates for MIP an initial lower bound of 177 to 180. The solution gap of MIP is on average 20%.
- CGH clearly outperforms MIP regarding runtime for problem instances with multiple depots and/or multiple trips. For instance, MIP runtime for problem instance 5 is more than 1,000 times higher compared to the CGH runtime (67 minutes vs. 4 seconds).
- Both, MIP and CGH solve the small problem instances with 10 planes optimally.

Analogous to the heterogeneous fleet results, the same conclusions can be drawn for the homogeneous fleet (see problem instance 6 to 10 in Table 2.2). The superiority of CGH in terms of runtime becomes even more evident in the homogeneous case. For instance, the runtime of problem instance 10 is 611,012 seconds for the MIP, while CGH requires only 3 seconds to find an optimal solution.

Therefore, the focus in the following is on the CGH test results for the larger problem instances with 25 and 50 planes and a heterogeneous tractor fleet. Table 2.3 summarize the test results of problem instances 11 to 20. The key observations are:

- Runtime is primarily driven by the number of planes to be served, the number of depots and the number of trips. Problem instances 16 to 20

Prob	# Pln	# Dpt	# Trp	T^{max}	# Trctr	MIP IP Val	MIP Gap* %	MIP LP Relax	MIP Time Sec	CGH IP Val	CGH Gap* %	CGH LP Relax	CGH Time Sec	CGH SP Sec
11	25	1	1	60	10/5	–	–	–	–	477	0.0	477.0	8	5
12	25	1	2	60	10/5	–	–	–	–	461	0.0	461.0	24	18
13	25	1	3	60	10/5	–	–	–	–	461	0.0	461.0	44	38
14	25	2	2	60	10/5	–	–	–	–	438	0.2	437.0	32	26
15	25	2	3	60	10/5	–	–	–	–	441	0.9	437.0	86	78
16	50	1	1	120	10/5	–	–	–	–	691	0.6	687.0	775	646
17	50	1	2	90	10/5	–	–	–	–	692	0.1	691.0	1,964	1,753
18	50	1	3	60	10/5	–	–	–	–	712	0.8	706.0	2,513	2,409
19	50	2	2	90	10/5	–	–	–	–	671	1.6	660.0	2,610	2,413
20	50	2	3	60	10/5	–	–	–	–	682	1.9	669.0	12,836	12,741

*Gap=(IP Value - LP Relax) / IP Value · 100

Table 2.3: Computational test results - Heterogeneous fleet, 25/50 planes

with 50 planes require the longest runtime of all instances. Again, the runtime increases with an additional depot (e.g. instance 16 with 646 seconds vs. instance 19 with 2,413 seconds) and additional trips (e.g. instance 19 with 2,413 seconds vs. instance 20 with 12,741 seconds).

- A large portion of the total runtime is consumed by solving SP, e.g. in problem instance 20, 99% of total runtime is accounted for solving SP. On average, 78% of total runtime is required to solve SP.
- CGH delivers good results. Feasible solutions derived by CGH deviate at most 1.9% from the lower bound. This is in line with the observation made in Desrochers et al. [25]. The authors present a column generation approach for the VRPTW and report an average integrality gap of 1.5%, see Bramel and Simchi-Levi [15] for an explanation of this behavior.

Figure 2.5 displays the development of the lower bound per iteration for problem instance 19 (50 planes, 2 depots, 2 trips, heterogeneous fleet). The ordinate show the objective value of the LP relaxation of RMP, the abscissae the iteration number. I conclude that CGH works well for the towing problem and the well-known tailing-off effect is negligible. SP runtime per iteration increases over time as displayed in Figure 2.6 for problem instance 19. The ordinate show the runtime of SP in seconds, the abscissae the iteration number. As previously mentioned, in the first 100 iterations SP is not solved optimally, but the first feasible solution with negative reduced costs is added to RMP. Thus, the runtime per iteration for the first 100 iterations is significantly lower than the runtime in the later stage.

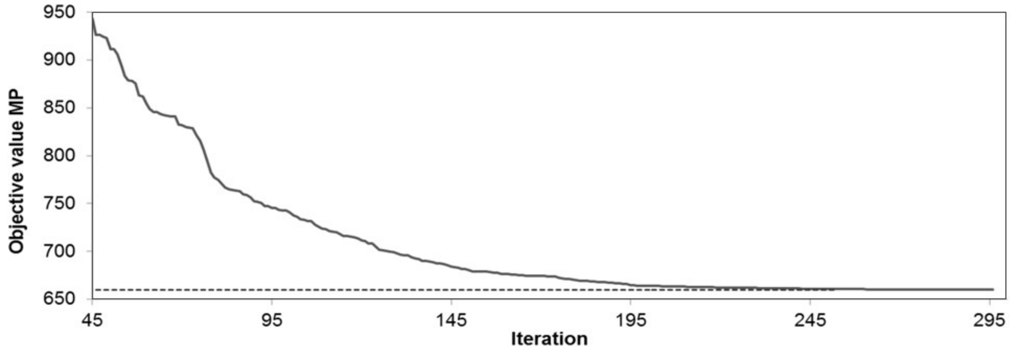

Figure 2.5: Development of the lower bound per iteration of problem instance 19

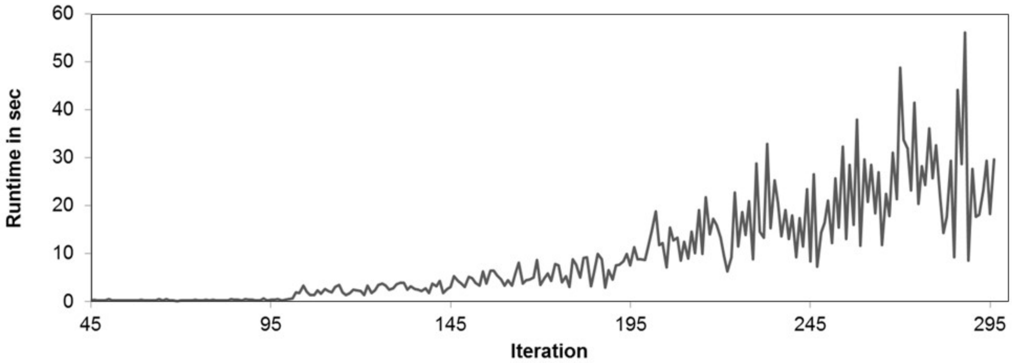

Figure 2.6: SP runtime per iteration of problem instance 19

2.5 Case study

The manual assignment of towing jobs to tractors is common practice at many airports. This section evaluates the cost efficiency of a manual schedule with regards to scheduling efficiency as well as efficiency of using the given fleet of tractors. This is done in two steps: In a first step I create an optimized schedule (schedule A) assuming that the fleet consists of those tractors, which have been used in the manual schedule. In a second step I examine the impact of extending the fleet to the full fleet available at the airport (schedule B).

I investigate 50 planes, which corresponds to roughly 3 working hours during a medium busy period of a day at the partner airport. According to the airport's infrastructure I take into account 2 depots, a maximum of

	Total variable costs in %	Delay costs in %	Travel costs in %	Service costs in %	Delay minutes	Travel minutes	Service minutes
Manual sched.	100	100	100	100	12	222	293
Schedule A	40	0	72	105	0	152	293
Schedule B	30	0	54	76	0	149	293

Table 2.4: Case study results - Variable costs and time

	# of tractors available	# of tractors used	VC of tractors in use in %
Manual schedule	23	14	100
Schedule A	14	10	105
Schedule B	23	10	80

Table 2.5: Case study results - Tractors

2 trips with a maximum trip length of 90 minutes. Table 2.4 and Table 2.5 summarize the case study results. Each line in the tables correspond to one schedule. For each schedule Table 2.4 shows the total variable costs, delay costs, travel costs and service costs as well as delay minutes, travel minutes and service minutes. In Table 2.5 the number of tractors available, the number of tractors used and the average variable costs of the used fleet is given for each schedule. Due to confidentiality reasons, not the absolute costs are given, but the relative costs compared to the manual schedule. Additionally, for each of the three schedules the travel time and variable costs per vehicle are shown in Figure 2.7. Each bar displays the travel time of one vehicle. Each sub-element of a bar indicates the travel time from one node to the next node. The normalized variable costs VC are given in brackets in the tractor labels. The variable costs of tractor 01 is set to 1. The ratio between the various variable costs corresponds to the real-world data.

The total costs and each cost component of the manual schedule is set to 100%. Although 14 tractors are in use, the manual schedule contains 12 delay minutes. These delays account for roughly 50% of the total variable costs. Schedule A assumes that the fleet consists of the same 14 tractors which have been utilized in the manual assignment. It took 655 seconds to find the near optimal solution (1.2% optimality gap). Compared to the manual schedule, the total variable costs of schedule A decreases by 60%, of which eliminating the delays account for roughly 90% of the total savings. Schedule A also reduces the travel time from 222 minutes to 152 minutes, i.e. the travel costs for schedule A is 20% lower than the travel costs of the manual schedule. Out of the 14 tractors employed in the manual schedule,

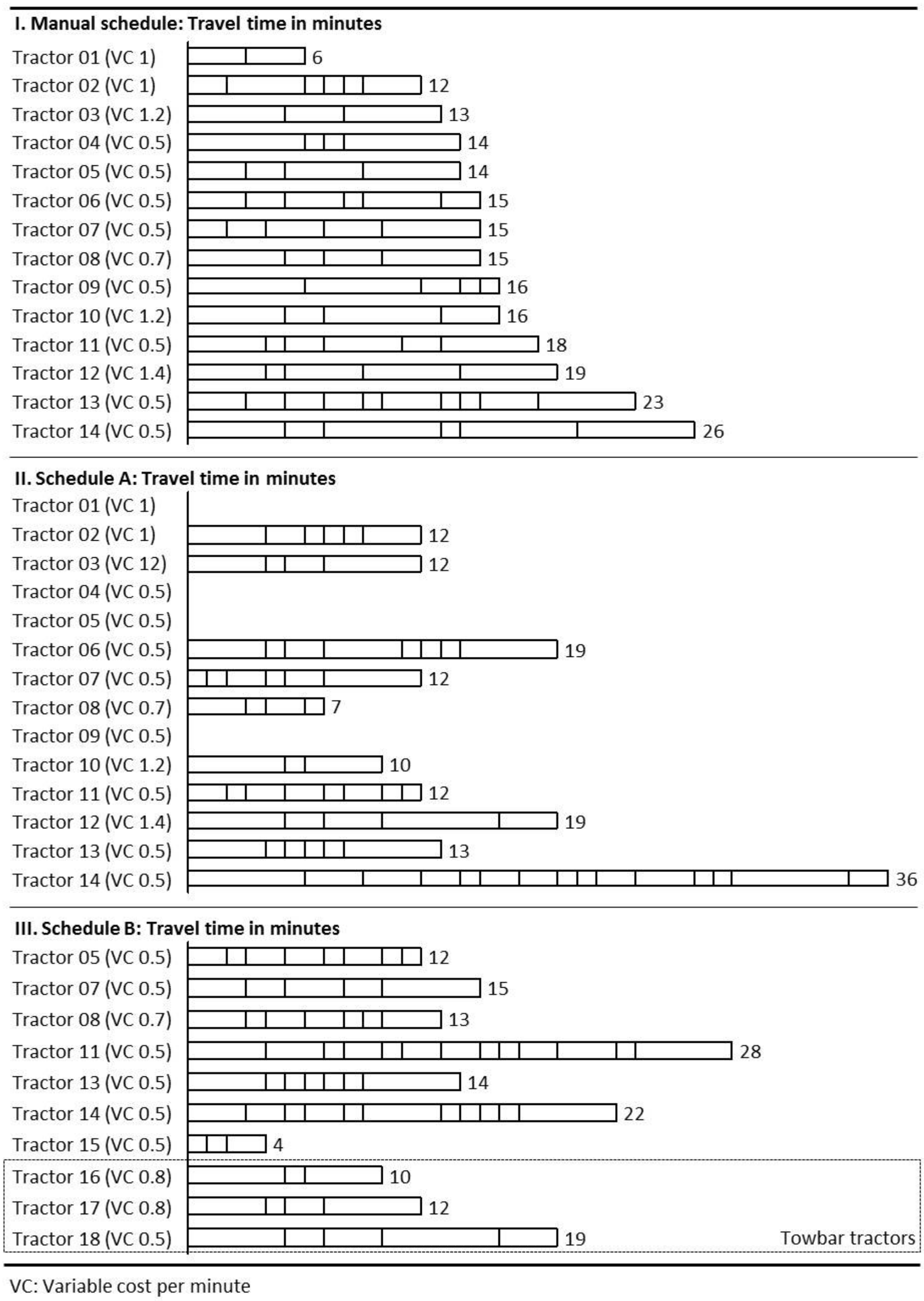

Figure 2.7: Overview travel time per tractor

schedule A utilizes 10 tractors only, but utilizes tractors with high flexibility (in terms of compatibility with plane types) and high variable costs. The average variable costs of the fleet utilized in schedule A is 5% higher than the average variable costs of the fleet used in the manual schedule. This impacts the service costs, which increases for schedule A by 5% compared to the manual schedule. Using at most 10 instead of 14 tractors at the same time indicates further savings potential in personnel costs which the objective function does not capture.

Schedule B considers the full fleet of 23 tractors, which is available at the airport. It takes 18 minutes to solve this problem instance and the objective function value of schedule B has an optimality gap of 1.8%. Schedule B results in a cost reduction by 70% compared to the manual schedule and 24% compared to schedule A. Like schedule A, schedule B eliminates all delays and utilizes 10 tractors. However, schedule B changes the tractors to a set of vehicles with lower variable costs (20% lower than the manual schedule). In the manual assignment, no towbar tractors are used. In contrast, schedule B utilizes 3 towbar tractors with high flexibility in terms of technical compatibility. Since the travel time reduces from schedule A to schedule B by 3 minutes only (152 minutes vs. 149 minutes) the total savings of 24% compared to schedule A can be attributed to a great extend to the new fleet mix.

Overall, the case study results emphasize on the importance of deciding on the optimal tractor mix for daily operations.

2.6 Summary

This chapter addresses the planning and scheduling of towing jobs at airports. The presented model assigns tractors to towing jobs. The objective function minimizes operating costs that vary by tractor type, subject to various operational restrictions and airport dependent specifications. Despite its practical relevance, this application area has been neglected in the literature thus far. The problem is stated as MIP based on the VRP. The model incorporating relevant operational restrictions and specifications such as time window, mixed fleet, multiple depots and multiple trips. I propose a column generation heuristic as solution procedure. The column generation heuristic finds (near) optimal solutions and is capable of solving problem instances with up to 50 planes, 2 depots and 3 trips, which corresponds to approximately 3 working hours at an international hub airport. In comparison, the original MIP formulation using a standard solver fails in solving such problems in reasonable time.

In a case study with data from a major European hub airport, I compare a manual schedule with an optimized schedule to gain insights on main cost drivers and characteristics of efficient schedules. Compared to the manual schedule, the optimized schedule contains no delays and reduces travel time by 33%.

Chapter 3

Fleet composition of towing tractors

For the operational planning problem in Chapter 2 I assume a set of given tractors, which can be assigned to towing jobs. This assumption holds true from a day-to-day operational perspective. However, in the long-term the towing service provider can define its fleet. Usually the fleet consists of a set of heterogeneous tractors. These towing tractors differ with respect to investment costs, variable costs and a technical compatibility with plane types. The optimal fleet size and mix is critical for a towing service provider to operate cost effective and fulfill service level agreements. This chapter introduces a model that generates a cost optimal (dis-)investment plan for a heterogeneous set of towing tractors considering a multi-year horizon. The model builds on a column generation approach (see Desaulniers et al. [24]). It consider a selling option, a general overhaul option, a minimum duration of use, a maximum lifetime and the technical compatibility of tractor types with plane types. The fleet size and mix can change from period to period. In the following, an "investment plan" in the broader sense refers to a plan which includes decision on buying, overhauling and selling, it can invest and divest.

The remainder of this chapter is organized as follows: I refer to related literature in the next section. In Section 3.2, I introduce the problem, explain the mathematical formulation and the solution approach. Section 3.3 presents an approach to aggregate demand using flight schedule information and describes how the existing fleet can be incorporated in the model. In Section 3.4 I demonstrate an application of the model in a real-world setting. For this purpose, I determine the investment plan for a major European airport. Additional scenario analyses investigate the impact of demand and cost deviations. I conclude with a summary of the main findings in Section 3.5.

3.1 Related literature

A Fleet Sizing Problem (FSP) determines the number of vehicles for a homogeneous fleet, while a Fleet Composition Problem (FCP) refers to the problem of deciding on the fleet size and mix for a heterogeneous set of vehicles (e.g. see Etezadi and Beasley [32]). FSP and FCP literature can be categorized in those considering routing and those ignoring routing. Hoff et al. [38] and Bielli et al. [13] provide an overview of papers combining FCP with vehicle routing, the so-called Fleet Size and Mix Vehicle Routing Problems (FSMVRP). The model proposed in this chapter does not include routing aspects, since I focus on a long-term strategic perspective. At a strategic level demand, costs and revenue uncertainties related to fleet operations are high, thus taking into account routing aspects on a detailed level is ineffective (see Hoff et al. [38]). Hoff et al. [38] recommend considering routing, e.g. in tactical settings of several months in road transportation. To the best of my knowledge, there is no FCP literature addressing the towing fleet composition problem that covers this specific problem in one model.

Kirby [42] and Wyatt [64] are among the first to address the FSP. Kirby [42] investigates the wagon fleet size of a railway system. He concludes that the ratio of days to hire external vehicles to own vehicles should be set to the ratio of costs of renting external vehicles to fixed costs of internal vehicles. Wyatt [64] considers a fleet of barges. He extends the idea of Kirby [42] by adding variable costs to the formula. Other examples of FSP papers are Alsbury [3], Parikh [54], Imai and Rivera [39] and Wu [63].

Papers investigating a heterogeneous fleet are Gould [37], Loxton et al. [47] and Redmer et al. [55]. In contrast to this work, their fleet composition is determined for one period only or are constant in all periods in these papers. Gould [37] formulates a linear programming model, which minimizes the total annual costs of a road transport department while satisfying demand with a seasonal pattern. The model takes into account fixed costs, variable costs and costs of hiring external vehicles. Loxton et al. [47] also present an approach which minimizes fixed, variable and hiring costs. The authors determine a fleet composition, in a setting, where the demand, given by the number of required vehicles per type, changes from period to period. The proposed algorithm combines dynamic programming and golden section search and solves instances with up 200 vehicle types within seconds. The work of Redmer et al. [55] determines an optimal fleet composition of road tankers for fuel distribution. The authors present two integer programming formulations of the problems and implement several heuristics. Finally, they compare the performance of the different formulations using their heuristic procedures.

Mole [50] and Simms et al. [59] allow a dynamic fleet size for a homogeneous fleet. Similar to Kirby [42] and Wyatt [64], Mole [50] determines the number of own vehicles, while minimizing fixed, variable and hiring costs. The author develops a dynamic programming model which determines the timing of investments in new vehicles in order to react to demand trends. Simms et al. [59] combines dynamic programming with linear programming to derive the optimal buy, operate and sell policy for buses.

New [51], Etezadi and Beasley [32], Couillard and Martel [21], Wu et al. [62] and Burt et al. [16] examine a planning horizon of several periods and allow fleet composition to change over time. None of these papers capture a general overhaul option and a minimum duration of use. New [51] presents a linear programming model,that minimizes the operating costs of an airline fleet by deciding on the timing of investment and scrap of planes. Etezadi and Beasley [32] propose a mixed integer program to determine the optimal fleet composition of vehicles which serve several customers from a central depot. The model minimizes the fixed and variable costs of own and hired vehicles, while ensuring a sufficient number of vehicles in each period to cover the distance to and capacity for all customers. Couillard and Martel [21] introduce a stochastic programming model to tackle the FCP for road carriers. The model determines the cost minimal purchase, sale and rental policy for a set of heterogeneous trucks, while demand is subject to seasonal fluctuations. It considers among others the age of vehicles in the fleet as well as tax allowances for owning a vehicle. Wu et al. [62] apply the FCP to the specifics of the truck-rental industry. The authors introduce a linear programming model, which decides on truck investment and disinvestment, demand allocation and repositioning of empty trucks. The solution procedure applies Benders decomposition and Lagrangian relaxation in a two stage approach, with which they can solve instances with 3 tractor types, 60 periods and 25 locations within 12 hours. The work of Burt et al. [16] investigates the FCP for the mining industry. The proposed integer program determines the optimal buy and sell policy for trucks and loaders used in a mining location. A unique aspect of this model is the consideration of compatibility between trucks and loaders. In a case study the authors determine the optimal solution for a problem with eight trucks, 20 loaders and 13 periods within 2.5 hours.

In summary, no literature specifically addresses the towing fleet composition at airports. The papers of New [51], Etezadi and Beasley [32], Couillard and Martel [21], Wu et al. [62] and Burt et al. [16] come closest to this work. A general overhaul option and the minimum duration of use are not included in any of the models. Furthermore, technical compatibility is in most cases not taken into account. Yet, these aspects are essential when determining the optimal investment strategy in a real-world towing setting.

3.2 Mathematical formulation and solution approach

The model introduced in the following generates a cost optimal multi-period investment plan for a set of heterogeneous towing tractors. It considers a planning horizon of $|\mathcal{T}|$ periods. The model determines for each tractor type b the number of required tractors in each period t in order to satisfy a demand $DM_{d,t}$ of each demand pattern d in period t. To fulfill demand, a tractor type b has to be technically compatible with demand pattern d, i.e. $CP_{b,d} = 1$. The model takes into account the existing fleet. NE_b denotes the number of available tractors of type b. The fleet size and mix can be adjusted from period to period by buying new tractors and overhauling or selling existing ones. A general overhaul is required, if a tractor is used beyond its maximum duration of use DU. A general overhaul extends a tractor's lifetime by additional AD periods. A tractor can be sold on the market if a tractor is not required anymore before reaching its maximum lifetime DU (without general overhaul) or $DU+AD$ (with general overhaul). However, a tractor has a minimum duration of use of MU periods, before it can be sold. MU does not reflect a technical feature of a tractor, but rather is set by the management. Buying, using, overhauling and selling a tractor is associated with costs and earnings, denoted in the model with investment costs IC_t, variable costs VC_t, overhaul costs OC_t and sales revenues SR_t. Cost changes and discount rate are important factors when considering a planning horizon of several years. Therefore, period index t is attached to all cost parameters. Both cost changes and the discount rate are incorporated in the cost data, and do not appear explicitly in the model. Note that the parameters DU, AD, MU, IC_t, VC_t, OC_t and SR_t are tractor type specific and assume different values for each tractor type b.

A Column Generation Heuristic (CGH) is used as solution approach. Column generation decomposes the problem into a Master Problem (MP) and a Subproblem (SP), which generates feasible columns. A feasible column $a \in A(b)$ represents one investment plan for a specific tractor type b. The investment plan contains the information in which periods the tractor should be used and accordingly when/if to buy, overhaul and sell this tractor. It takes into account restrictions such as the maximum lifetime AD or the minimum duration of use MU before a tractor can be sold. $A(b)$ is the set of all investment plans associated with tractor type b. Each investment plan $a \in A(b)$ is associated with total investment plan costs of $TC_{b,a}$.

MP determines the fleet size and mix by selecting which investment plan to follow. It minimizes the costs while ensuring demand satisfaction. Only a subset of all feasible investment plans are considered and new columns are added iteratively. The procedure starts with a small subset of columns and solves the LP relaxation of the Restricted Master Problem (RMP). By inserting the dual value information of RMP constraints into the objective function of SP, a promising absent columns is generated. Those columns are added to RMP and the LP relaxation of RMP is resolved. The procedure terminates with a lower bound for the problem. In a second step, all available columns which have been inserted in RMP thus far are taken and RMP is solved as IP to generate a feasible solution.

Master Problem. The notation and mathematical formulation of MP are as follows:

Sets:

$\mathcal{B}$	Set of tractor types (index b)
$\mathcal{A}(b)$	Set of investment plans associated with tractor type b (index a)
$\mathcal{D}$	Set of demand patterns (index d)
$\mathcal{T}$	Set of periods (index t)

Parameters:

$TC_{b,a}$	Costs of investment plan a associated with tractor type b
CW	Costs associated with auxiliary variable $w_{d,t}$
$CP_{b,d}$	1, if tractor type b is compatible with at least one plane type associated with demand pattern d, 0 otherwise
$X_{b,a,t}$	1, if investment plan a for tractor type b covers period t, 0 otherwise
$DM_{d,t}$	Demand of demand pattern d in period t

NE_b Number of existing tractors of tractor type b

Variables:

$\lambda_{b,a}$ Number of tractors of type b bought and sold according to investment plan a

$w_{d,t}$ Number of external tractors to cover demand pattern d in period t

$$\text{Minimize} \sum_{b \in \mathcal{B}} \sum_{a \in \mathcal{A}(b)} TC_{b,a} \cdot \lambda_{b,a} + CW \cdot \sum_{d \in \mathcal{D}} \sum_{t \in \mathcal{T}} w_{d,t} \tag{7a}$$

subject to

$$\sum_{\substack{b \in \mathcal{B}: \\ CP_{b,d}=1}} \sum_{a \in \mathcal{A}(b)} X_{b,a,t} \cdot \lambda_{b,a} + w_{d,t} \geq DM_{d,t} \qquad \forall d \in \mathcal{D}, t \in \mathcal{T} \tag{7b}$$

$$\sum_{a \in \mathcal{A}(b)} \lambda_{b,a} \geq NE_b \qquad \forall b \in \mathcal{B} \tag{7c}$$

$$\lambda_{b,a} \geq 0 \text{ and integer} \qquad \forall b \in \mathcal{B}, a \in \mathcal{A}(b) \tag{7d}$$

$$w_{d,t} \geq 0 \text{ and integer} \qquad \forall d \in \mathcal{D}, t \in \mathcal{T} \tag{7e}$$

The objective function (7a) minimizes the total costs of all tractors used according to the selected investment plans. The first sum adds the costs of all investment plans $TC_{b,a}$ which are selected. The auxiliary variables $w_{d,t}$ in the second sum guarantee feasibility in the course of the column generation procedure and are required to initialize RMP. They can be interpreted as number of external tractors to cover demand pattern d in period t. The use of external tractors is penalized with costs CW. Since renting external tractors is not practical in reality, CW is set to a value, which is higher than the most expensive column costs.

Demand constraints (7b) ensure that the demand in each period is fulfilled for each demand pattern, i.e. there must be sufficient numbers of compatible tractors to satisfy demand. Variable $\lambda_{b,a}$ denotes the number of tractor type b which are bought, overhauled and sold according to investment plan a. The auxiliary variables $w_{d,t}$ again ensure feasibility and can be interpreted as number of external tractors used.

Constraints (7c) take the existing fleet into account. For each existing tractor I create one additional SP and adapt decision variable settings in SP and parameter settings (see Section 3.3.3). Thus, one tractor type might be represented by several SP. Constraints (7c) enforce NE_b number of investment plans of tractor type b to be selected. NE_b is greater than or equal to 1 for SP representing existing tractor types and NE_b is 0 for all other SP. Variable definitions are given in (7d) and (7e).

The dual solution of RMP is obtained by relaxing the integrality conditions and solving RMP with a subset of columns. Let $\delta_{d,t} \geq 0$ denote the dual values of constraints (7b), then $\delta_t \geq 0$ is defined as

$$\delta_t = \sum_{d \in \mathcal{D}} \delta_{d,t} \ \forall t \in \mathcal{T}. \tag{8}$$

And let $\tilde{\delta}_b \geq 0$ denote the dual values of constraints (7c). Then the reduced costs of column a associated with tractor type b is

$$\bar{c}_{b,a} = TC_{b,a} - \left(\sum_{t \in \mathcal{T}} \delta_t \cdot X_{b,a,t} + \tilde{\delta}_b \right) \tag{9}$$

with $TC_{b,a}$ representing the total costs of investment plan a for tractor type b defined as:

$$\begin{aligned} TC_{b,a} = & \sum_{t \in \mathcal{T}} VC_t \cdot X_{b,a,t} + \sum_{t \in \mathcal{T}} IC_t \cdot Y^{\text{buy}}_{b,a,t} \\ & + O^{\text{cost}}_{b,a,t} - \sum_{t \in \mathcal{T}} \sum_{\tilde{t} \in T} SR_{\tilde{t}} \cdot U_{b,a,t,\tilde{t}} \end{aligned} \tag{10}$$

$X_{b,a,t}, Y^{\text{buy}}_{b,a,t}, O^{\text{cost}}_{b,a,t}$ and $U_{b,a,t,\tilde{t}}$ represent the variables values in SP. A detailed description of the cost components can be found in the explanation of SP's objective function (see (11a)). LP optimality of RMP is reached when $\bar{c}_a \geq 0$ holds for all absent columns $a \notin \mathcal{A}(b)$ associated with any tractor type $b \in \mathcal{B}$. Whenever a new column is found with negative reduced costs (i.e. the objective value of SP is negative), this column is added to RMP and a new iteration starts. The procedure terminates when no further column has negative reduced costs.

Subproblem (b). One SP(b) is created for each tractor type and each existing tractor. Each SP(b) generates investment plans for tractor type b. Following additional notation is used to formulate SP(b):

Parameters

VC_t	Variable costs in period t
IC_t	Investment costs in period t
SR_t	Sales revenue for one remaining use period, if tractor is sold in period t
OC_t	General overhaul costs in period t
DU	Maximum duration of use without general overhaul
AD	Maximum additional duration of use after a general overhaul
MU	Minimum duration of use before tractor can be sold

Variables

x_t	1, if tractor is used in period t, 0 otherwise and $x_0 = 0, x_{\lvert\mathcal{T}\rvert} = 0$
y_t^{buy}	1, if tractor is bought in period t, 0 otherwise
y^{ov}	1, if tractor is overhauled, 0 otherwise
y_t^{sell}	1, if tractor is sold in period t, 0 otherwise
$u_{t,\tilde{t}}$	Remaining lifetime if tractor is bought in period t and sold in period $\tilde{t}$
o_t^{cost}	Costs of general overhaul if tractor is bought in period t

The mathematical formulation of SP(b) then looks as follows:

$$\begin{aligned}\text{Minimize } & \sum_{t\in\mathcal{T}} VC_t \cdot x_t + \sum_{t\in\mathcal{T}} IC_t \cdot y_t^{\text{buy}} + \sum_{t\in\mathcal{T}} o_t^{\text{cost}} \\ & - \sum_{t\in\mathcal{T}} \sum_{\tilde{t}\in\mathcal{T}} SR_{\tilde{t}} \cdot u_{t,\tilde{t}} - \left(\sum_{t\in\mathcal{T}} \delta_t \cdot x_t + \tilde{\delta}_b \right)\end{aligned} \tag{11a}$$

subject to

$$x_{t-1} + y_t^{\text{buy}} \leq 1 \qquad \forall t \in \mathcal{T} \tag{11b}$$
$$x_t - x_{t-1} - y_t^{\text{buy}} \leq 0 \qquad \forall t \in \mathcal{T} \tag{11c}$$
$$-x_{t-1} + y_t^{\text{sell}} \leq 0 \qquad \forall t \in \mathcal{T} \tag{11d}$$
$$x_t + y_t^{\text{sell}} \leq 1 \qquad \forall t \in \mathcal{T} \tag{11e}$$
$$-x_t + x_{t-1} - y_t^{\text{sell}} \leq 0 \qquad \forall t \in \mathcal{T} \tag{11f}$$

$$y^{\text{ov}} \leq \sum_{t \in \mathcal{T}} y_t^{\text{buy}} \tag{11g}$$

$$\sum_{\tilde{t} \in \mathcal{T}} \tilde{t} \cdot y_{\tilde{t}}^{\text{sell}} - \sum_{t \in \mathcal{T}} t \cdot y_t^{\text{buy}}$$
$$\geq (DU + 1) \cdot y^{\text{ov}} \tag{11h}$$

$$o_t^{\text{cost}} \geq OC_{t+DU} \cdot (y_t^{\text{buy}} + y^{\text{ov}} - 1) \quad \forall t \in \{1, ..., |\mathcal{T}| - DU\} \tag{11i}$$

$$u_{t,\tilde{t}} \leq (DU + AD) \cdot y_t^{\text{buy}} \quad \forall t, \tilde{t} \in \mathcal{T} \tag{11j}$$

$$u_{t,\tilde{t}} \leq (DU + AD) \cdot y_{\tilde{t}}^{\text{sell}} \quad \forall t, \tilde{t} \in \mathcal{T} \tag{11k}$$

$$u_{t,\tilde{t}} \leq AD \cdot y^{\text{ov}} + DU - (\tilde{t} \cdot y_{\tilde{t}}^{\text{sell}} - t \cdot y_t^{\text{buy}}) + \tilde{t} \cdot (1 - y_t^{\text{buy}}) \quad \forall t, \tilde{t} \in \mathcal{T} \tag{11l}$$

$$\sum_{t \in \mathcal{T}} y_t^{\text{buy}} \leq 1 \tag{11m}$$

$$x_{\tilde{t}} \geq y_t^{\text{buy}} \quad \forall t \in \{1, ..., |\mathcal{T}| - 1\}, \tilde{t} \in \{t, ..., min\{t + MU - 1, |\mathcal{T}| - 1\}\} \tag{11n}$$

$$1 - x_{t+DU+AD} \geq y^{\text{ov}} + y_t^{buy} - 1 \quad \forall t \in \{1, ..., |\mathcal{T}| - 1 - AD - DU\} \tag{11o}$$

$$1 - x_{t+DU} \geq y_t^{\text{buy}} - y^{\text{ov}} \quad \forall t \in \{1, ..., |\mathcal{T}| - 1 - DU\} \tag{11p}$$

$$x_t, y_t^{\text{buy}}, y^{\text{ov}}, y_t^{\text{sell}} \in \{0; 1\} \quad \forall t \in \mathcal{T} \tag{11q}$$

$$o_t^{\text{cost}}, u_{t,\tilde{t}} \geq 0 \quad \forall t, \tilde{t} \in \mathcal{T} \tag{11r}$$

The objective function (11a) minimizes the reduced costs of a new investment plan. It takes into account (I) the variable costs of all periods in which a tractor is used. The variable costs per period VC_t for a tractor type b can be obtained by multiplying the variable costs per minute with the target utilization time. Furthermore, it considers (II) the investment costs IC_t if a tractor is bought and (III) the overhaul costs o_t^{cost} in case of a general overhaul. If a tractor is sold (IV) the earnings are deducted. The earnings depend on the remaining lifetime $u_{t,\tilde{t}}$ and the sales revenue for one remaining use period SR_t. I assume a liquidation of all tractors at the end of the planning horizon. Finally, (V) the dual values δ_b and $\tilde{\delta}_b$ obtained from solving relaxed RMP are deducted.

Constraints (11b) and (11c), together with constraints (11n) detect a shift of the x variable from 0 to 1 and thereby determine the buying period. These constraints are the linearization of $y_t^{\text{buy}} = x_t \cdot (1 - x_{t-1})$. Accordingly, constraints (11d), (11e) and (11f) detect a shift of the x variable from 1 to

0, which determines the selling period. Again, these constraints linearize $y_t^{\text{sell}} = x_{t-1} \cdot (1 - x_t)$.

Constraints (11g), (11i) and (11h) set the rules for a general overhaul: A general overhaul can only take place, if the tractor has been bought previously (11g) and before the tractor is being sold (11h). Variable $y^{\text{ov}} = 0$, if the tractor is sold before the maximum duration of use DU is reached. Constraints (11i) determine the overhaul costs. A general overhaul takes place at the end of the tractor's lifetime, i.e. in period $t + DU$ if the tractor has been bought in period t. Therefore, o_t^{cost} is set to OC_{t+DU} if $y_t^{\text{buy}} = 1$ and $y^{\text{ov}} = 1$. Here, OC_{t+DU} denote the costs of a general overhaul, if this overhaul takes place in period $t + DU$. In all other periods, o_t^{cost} is set to 0 since costs are minimized in the objective function.

Constraints (11j), (11k) and (11l) track the remaining number of periods a tractor can be used (remaining lifetime). The remaining lifetime depends on the period t in which the tractor is bought and the period $\tilde{t}$ in which the tractor is sold. $u_{t,\tilde{t}}$ is set to 0 for all periods, a tractors was not bought (11j) or sold (11k). While in the periods, in which the tractor is bought or sold, $u_{t,\tilde{t}}$ is limited to an upper bound of $DU + AD$. For the period t in which the tractor is bought and the period $\tilde{t}$ in which the tractor is sold, $u_{t,\tilde{t}}$ is set to $AD + DU - \tilde{t} + t$ (with general overhaul) or $DU - \tilde{t} + t$ (without general overhaul), which equals the remaining lifetime (11l).

Constraint (11m) ensures that the tractor is bought not more than once. Constraints (11n) enforce the use of a tractor once it was bought. The x variable is set to 1 for the period a tractor is bought and the following periods until the minimum usage duration MU or the end of the planning horizon is reached. For example, if a tractor is bought in period 1 and the minimum duration of use MU is 4 periods, x takes the value of 1 for periods 1, 2, 3 and 4. If the tractor is bought in period 8 and $|\mathcal{T}| = 11$, then x is set to 1 for periods 8, 9 and 10. Note, the last period is added only to liquidate remaining tractors, i.e. $DM_{d,|\mathcal{T}|} = 0$, $\forall d \in \mathcal{D}$. Thus, the model considers 21 periods for a planning horizon of 20 periods.

Constraints (11o) and constraints (11p) ensures that the maximum duration of use is not exceeded. In constraints (11o) the maximum duration of use equals the initial lifetime DU of a tractors plus the additional duration of use AD due to a general overhaul. The constraints set the variable x in period $t + DU + AD$ to 0, if a general overhaul takes place in period $t + DU$. For example, if $DU = AD = 4$ and the tractor is bought in period 1 ($y_1^{buy} = 1$), then constraints (11o) enforce x_9 to take the value 0. In the second case no general overhaul takes place (11p), therefore the maximum duration of use corresponds to the initial lifetime DU of the tractors. Variable definitions are given in (11q) - (11r).

t	1	2	3	4	5	6	7	8	9	10
x_t	0	**1**	**1**	**1**	**1**	**1**	**1**	0	0	0
y_t^{buy}	0	**1**	0	0	0	0	0	0	0	0
y_t^{ov}	0	0	0	0	0	**1**	0	0	0	0
y_t^{sell}	0	0	0	0	0	0	0	**1**	0	0
y^{ov}	1									
$u_{2,8}$	2									
$TC_{b,a}$	1,305,289									

Table 3.1: Example investment plan a for tractor type b

Table 3.1 gives an example of an investment plan a for tractor type b. The table shows the values of the decision variables and the total investment plan costs $TC_{b,a}$ in the periods P1 to P10. The maximum lifetime DU is 4 periods and the additional lifetime after a general overhaul is 4 periods. According to the investment plan, the tractor is used in periods 2 to 7. y^{buy} is set to 1 in the period, in which there is a shift from 0 to 1 in the x variable, here $y_2^{buy} = 1$. Accordingly, y^{sell} is set to 1 if there is a shift from 1 to 0 in the x variables, i.e. $y_8^{sell} = 1$. The maximum lifetime is reached and requires a general overhaul, i.e. $y^{ov} = 1$. The remaining lifetime of this tractors, which was bought in period 2 and sold in period 8, is 2 periods, i.e. $u_{2,8} = 2$, $u_{t,\tilde{t}} = 0$ in all other periods $t, \tilde{t}$.

The solution of SP(b) is a new investment plan (column) in RMP. Particularly, the new column a associated with tractor type b is given as

$$\begin{bmatrix} TC_{b,a} \\ \overrightarrow{X}_{b,a} \\ \mathbf{1}_b \end{bmatrix}$$

where $TC_{b,a}$ is the total costs of investment plan a associated with tractor type b. $\overrightarrow{X}_{b,a}$ is a vector with $|\mathcal{T}|$ elements indicating in which periods the tractor is used, or in other words containing the values of the decision variable x_t of SP(b), i.e. $X_{b,a,t} = x_{b,t}\ \forall t \in \mathcal{T}$. $\mathbf{1}_b$ is a unit vector with length

$|\mathcal{B}|$ and value 1 at position b and else 0. To find a feasible solution, all columns that have been generated when solving the LP relaxation of RMP are used and RMP is solved as IP.

3.3 Demand and fleet related input data

In the following, I introduce a procedure for demand aggregation based on a flight schedule and present an example of demand forecasting. Moreover, I explain how the existing fleet can be incorporated in the model.

3.3.1 Demand pattern generation

Constraints (7b) in MP ensure in each period a sufficient number of compatible tractors to satisfy demand. The demand for a period is expressed by a set of demand patterns. One period equals a winter or summer flight schedule, i.e. 6 months. The procedure for demand pattern generation is summarized in Table 3.2. In the following, I explain the four steps of demand pattern generation from a given flight schedule for one period.

Repeat for all periods $t \in \mathcal{T}$
Input: Flight schedule period t
Step 1: Select a representative peak day in period t
Step 2: Determine for each job of selected day tractor occupation time
Step 3: Repeat for all plane type
i) Determine for each time interval the number of simultaneous jobs
ii) Determine the daily maximum of number of simultaneous jobs
Step 4: Determine sum of results from step 2 for
plane types with overlapping tractor compatibility structure
Output: Demand $DM_{d,t}$ of demand pattern d of period t

Table 3.2: Procedure for demand pattern generation

Step 1: Select a representative peak day in the period. Within a summer or winter flight schedule the days usually are nearly identical in terms of departure times and plane types.

Step 2: Calculate the time window of tractor occupancy for each towing job of the selected day. The occupancy time comprises a travel time, waiting time and processing time. The upper part of Figure 3.1

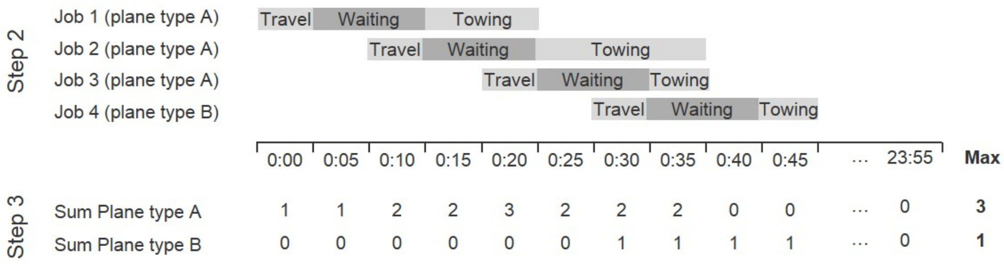

Figure 3.1: Step 2 and step 3 - Tractor occupancy time per job and maximum number of simultaneous jobs

visualizes the outcome of step 2. The horizontal axis refers to the time of the day, each row refers to one towing job. The bars shows the occupation time of a tractor for each job. In the case study in Section 3.4 I set the time interval length to five minutes. The average travel time of 5 minutes, average waiting time of 10 minutes and real processing times are derived from real-world data and are rounded to fit the time interval. The length of the time interval does not influence the number of demand patterns and therefore has no impact on the size of the model.

Step 3: Determine the number of simultaneous jobs for each time interval and derive the maximum of the day per plane type. The lower part of Figure 3.1 is a table showing for each plane type (rows) and each time interval (columns) the number of simultaneous jobs. The last column at the right displays the daily maximum for each plane type. In this example, the daily maximum of plane type A is 3, i.e. a maximum of 3 jobs is running simultaneously related to plane type A during the day. The model generates one demand constraint for each plane type. For example, the demand constraint for the first row ensures that the number of tractors compatible with plane type A is equal to or greater than 3.

Step 4: Ensure the aggregated demand of plane types is satisfied for overlapping tractor compatibility structures. In some cases it is not sufficient to ensure demand satisfaction for each plane type separately. If tractor compatibility overlaps, one tractor might be used for several jobs at the same time. There are three cases:

- **Case 1.** There is no overlap of tractor compatibilities. In Table 3.3 plane type A is compatible with tractor type 1 and 2, while plane type B is compatible with tractor type 3. Here one constraint per plane type as done in step 3 is sufficient. This results in two relevant demand constraints.

Tractor type	1	2	3
Plane type A	✓	✓	
Plane type B			✓

Table 3.3: Step 4 - Compatibility structure case 1

- **Case 2.** The compatibility structure of one plane type is a subset of the compatibility structure of another plane type. In Table 3.4 plane type A is compatible with all tractor types, and plane type B is only compatible with tractor type 2, i.e. the compatibility structure of plane type B is a subset of plane type A. In this case one additional demand constraint is required to ensure the number of tractors compatible with plane types A or B (here tractor types 1, 2 and 3) to be equal to or greater than the sum of the maximum number of simultaneous jobs for plane types A and B (here 4). This additional constraint makes the constraint for plane type A from step 3 redundant. This results in two relevant demand patterns: B and A+B.

Tractor type	1	2	3
Plane type A	✓	✓	✓
Plane type B		✓	

Table 3.4: Step 4 - Compatibility structure case 2

- **Case 3.** There is an overlap of tractor compatibility without subset structure. An example is given in Table 3.5. Here plane type A is compatible with tractor type 1 and 2 and plane type B is compatible with 2 and 3, i.e. both plane types are compatible with 2. This results in three relevant demand patterns: A, B and A+B. In this example I assume two plane types, for n plane types the number of relevant demand patterns is $\sum_{k=1}^{n} \frac{n!}{(n-k)!k!}$.

3.3.2 Demand forecasting

A key driver for fleet size and mix is demand. Therefore, a high quality demand forecasting as input is essential for a reliable investment plan as output. Demand, and thus demand patterns, are primarily influenced by

Tractor type	1	2	3
Plane type A	✓	✓	
Plane type B		✓	✓

Table 3.5: Step 4 - Compatibility structure case 3

three factors: I) The total number of towing jobs per day, II) the plane type mix and III) the number of towing jobs at each time of the day (in the following called "temporal distribution").

In the following, I present an example of demand forecasting for a major European hub airport. The data is used as input for the case study in Section 3.4. All relevant information for generating the demand patterns is available for the first two periods of the planning horizon in the case study (flight schedule summer 2013 and winter 2013/14). I use the following approach and assumptions to derive the demand for the following periods:

Table 3.6: Forecasting of numbers of towing jobs per day

	2013	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**
Summer	554	566	579	592	605	617	630	643	656	668	
Winter		552	564	576	589	601	614	626	638	651	663

i) The forecast for the number of towing jobs is based on the forecast for the number of flight movements. We assume a constant ratio between the number of flight movements to the number of push-backs, repositionings and maintenance towings (0.8 , 0.11 and 0.09 for the winter schedule and 0.83, 0.09 and 0.08 for the summer schedule). The forecasts for the number of towing jobs per day is displayed in Table 3.6. The table gives the forecast of the number of towing jobs for one peak day in summer 2013 to 2022 and winter 2014 to 2023. Note that winter 2014 refers to winter 2013/14. The number of towing jobs is expected to increase at a compounded annual growth rate (CAGR) of 2%.

ii) and iii) To derive changes in the plane mix and the temporal distribution of towing jobs, I rely on the standard flight schedule 2020, which is available for the partner airport. The standard flight schedule 2020 does incorporate a change in the plane mix. Other relevant sources for the future development of the fleet mix are amongst others Airbus S.A.S. [1] and Boeing Commercial Airplanes [14]. Real processing times were used as input data for flight schedule summer 2013 and winter 2014. For flight schedule

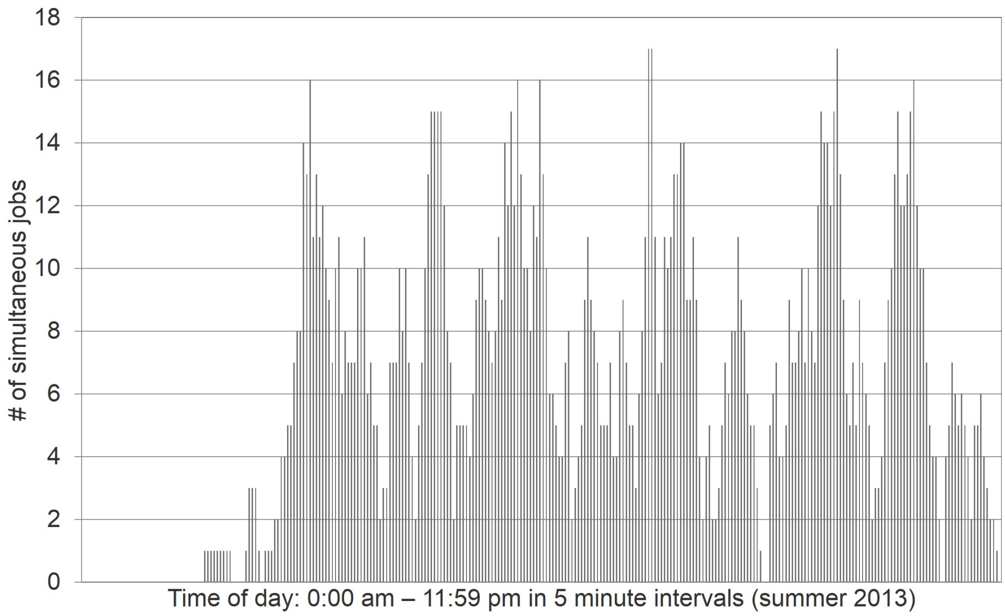

Figure 3.2: Temporal distribution of jobs (summer 2013)

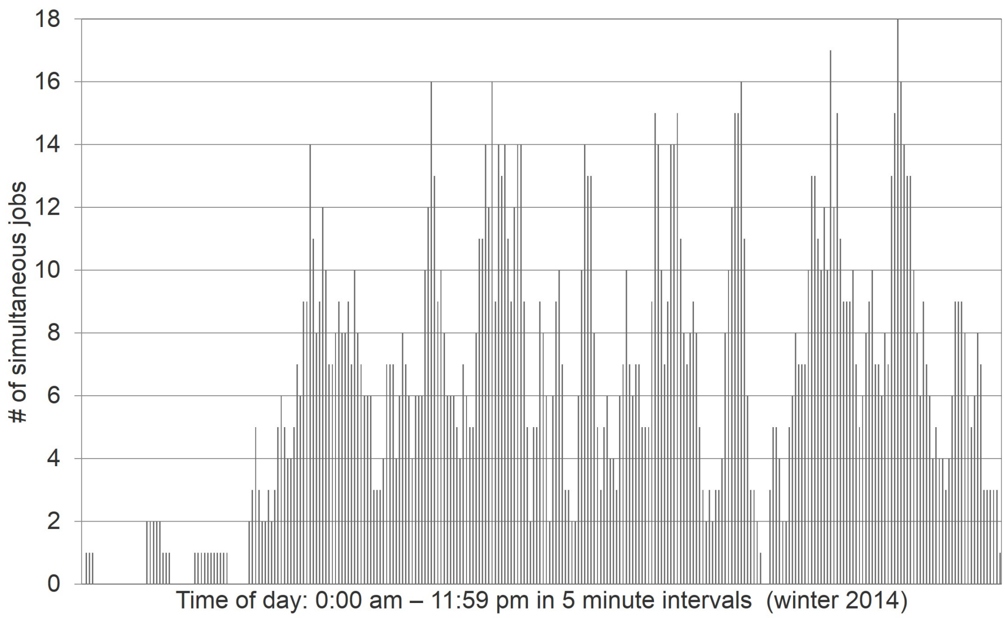

Figure 3.3: Temporal distribution of jobs (winter 2014)

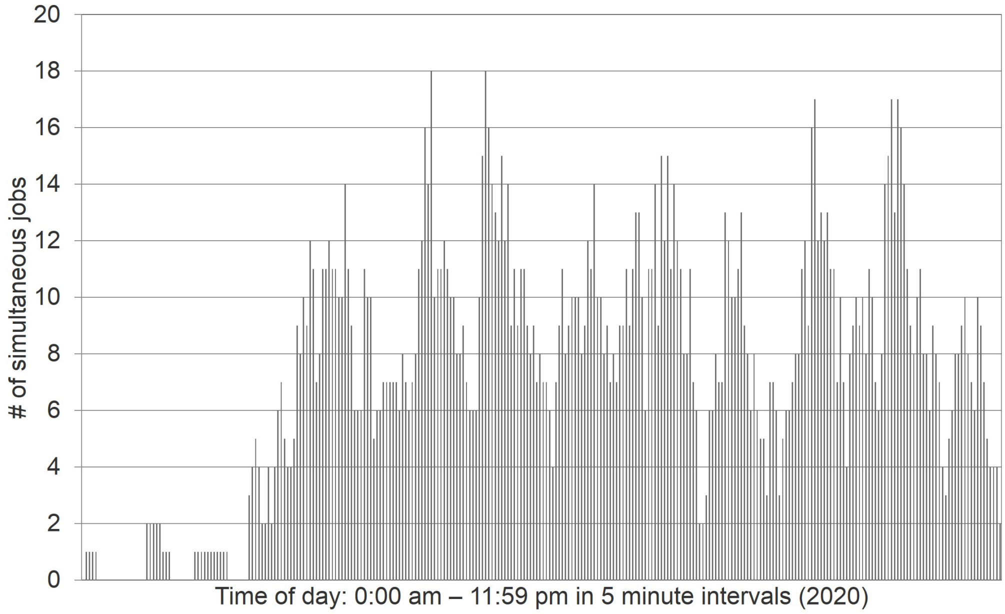

Figure 3.4: Temporal distribution of jobs (2020)

2020 I assume the average processing time. Furthermore, I assume the temporal distributions of maintenance towings and repositionings to remain the same as in 2013 and 2013/14. Based on these assumptions the temporal distribution of towing jobs in a day is visualized in Figure 3.2 (summer flight schedule 2013), Figure 3.3 (winter flight schedule 2013/14) and Figure 3.4 (2020). These figures show the total number of simultaneous jobs on the ordinate and time of the day on the abscissae. This information is available for each plane type. I assume a linear growth of the temporal distribution and change in plane type mix from summer 2013 and winter 2014 towards the distribution in 2020 and a constant distribution thereafter. Since the distribution 2020 is not divided into winter and summer, I assume the same distribution for both seasons. This assumption seems reasonable since the temporal distribution of the schedule summer 2013 and winter 2014 resemble each other (see Figure 3.2 and 3.3).

By combining the i) total number of jobs per day, ii) plane type mix and iii) temporal distribution, all relevant input data are available to generate the demand patterns for the forecasting periods.

3.3.3 Consideration of the existing fleet

A workable investment plan needs to take into account the existing fleet. The fleet can be distinguished between three tractor categories. The pool of potential tractor types on the market is category 1. For each tractor type, one SP is created. Category 2 are the pool of existing tractors without decision options. These are primarily tractors, which have a remaining lifetime of one or two periods. Each category 2 tractor is inserted directly as a column in MP and the selection of the column is ensured. Category 3 are existing tractors with decision options, i.e. the decision regarding an overhaul or selling has not been made yet. One additional SP is created and parameter and decision variable settings are adapted for each tractor type in category 3. For instance, if a tractor is bought in summer 2012, I set $y_1^{buy} = 1$, i.e. the tractor has to be bought in the first period of the planning horizon (in the case study summer 2013). Furthermore, I decrease the lifetime DU and investment costs IC_t for those two periods, which are not in the model's planning horizon. Constraints (7c) in MP ensure the selection of NE number of columns from this SP(b) in the final solution.

3.4 Case study

This section illustrates the application of the model at a major European airport. I derive an investment plan for a planning horizon of ten years. Additional scenarios demonstrate the robustness of investment decisions with respect to changes in demand, flight schedule disruptions and costs.

IBM ILOG CPLEX Optimization Studio 12.2 is used to code and solve MP and SP. All computations are performed on a 3.3 GHz PC (Intel(R) Core(TM) i3-2120 CPU) with 4 GB RAM running under the Windows 7 operating system. For the basic scenario with a problem size of 22 SPs, 21 periods and 76 demand patterns, the CGH obtains an optimal solution within 5 minutes. All other instances are solved to optimality with a runtime of between 3 and 37 minutes; the average runtime across all instances is 7 minutes. Column generation terminates with a lower bound for the optimal solution. Solving RMP as IP led to the same values as the lower bound. Therefore, I conclude on the optimality of the feasible solutions obtained from CGH.

3.4.1 Basic scenario

The parameters in the basic scenario are derived from real-world data and exhibited in Table 3.7:

Selling price SP_t	70% of investment costs
General overhaul costs OC_t	60%-80% of investment costs
Minimum duration of use MU	6 periods
Maximium duration of use DU	10 periods
Additional lifetime after overhaul AD	11 periods
Waiting time per job	10 minutes
Average utilization per tractor and day	5 hours

Table 3.7: Parameter settings and input data for the basic scenario

The optimal solution in the basic scenario is displayed in Figure 3.5. The four parts of the figure show the number of tractors to be used, bought, sold and overhauled for tractor types T01 to T13 in periods 1 to 20. In total, 55 tractors are bought, 11 tractors are sold and 10 tractors are overhauled. I only list tractors in the table which really are sold on the market, i.e. tractors with a positive remaining lifetime $u_{t,\tilde{t}} \geq 0$ and sold in periods 1 to 20. The sum of tractor periods is 371. If all 55 bought tractors were to be overhauled and kept until the end of their lifetime, the sum would be 816. Thus, the average duration of use per tractor is approximately seven periods, while the average potential duration of use including general overhaul is approximately 15 periods.

Figure 3.6 visualizes the number of tractors to be bought and sold over time. Figure 3.7 shows the number of tractors in use per period and tractor type and Figure 3.8 displays the number of tractors to be used per period and in the categories of "existing" versus "new" tractors (see Section 3.3.3). The abscissae refers to the period, the ordinate to the number of tractors bought, sold or used. After looking at the figures, two conclusions can be drawn: First, there is a clear preference for certain tractor types, namely T10, T12 and T13. The fleet mix is dominated by these three tractor types starting from period 7. From period 13 onwards, the fleet consists of only these three tractor types. In particular, T10 and T12 are characterized by high flexibility in terms of technical compatibility, while T13 has comparatively low investment and variable costs. Second, the current number of existing tractors is too high: In the first period, the number of tractors used is predetermined by the existing fleet. With a reduction in the existing fleet

	Period	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	Total
Use	T 01	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
	T 02	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6
	T 03	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6
	T 04	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
	T 05	4	2	2	2	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	16
	T 06	3	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	13
	T 07	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
	T 08	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
	T 09	4	4	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12
	T 10	1	2	2	3	3	3	4	4	4	7	7	7	7	7	6	6	6	6	5	6	96
	T 11	3	3	3	3	3	3	1	1	1	1	1	1	0	0	0	0	0	0	0	0	24
	T 12	1	1	1	1	1	1	2	2	2	1	1	1	1	2	2	3	2	3	3	3	34
	T 13	2	4	5	6	6	8	8	9	8	8	6	9	8	9	10	9	10	9	11	11	156
	Total	25	20	18	20	18	20	17	18	17	19	16	18	16	18	18	18	18	18	19	20	371
Buy	T 01	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
	T 02	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
	T 03	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
	T 04	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
	T 05	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
	T 06	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
	T 07	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
	T 08	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
	T 09	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
	T 10	1	1	0	1	0	0	1	0	0	3	0	0	0	0	0	0	0	0	0	1	8
	T 11	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
	T 12	1	0	0	0	0	0	1	0	0	0	0	0	0	1	0	1	0	1	0	0	5
	T 13	2	2	1	1	0	2	0	1	0	0	0	4	0	2	1	1	1	0	2	0	20
	Total	25	4	1	2	0	2	2	1	0	3	0	4	0	3	1	2	1	1	2	1	55
Sell	T 01	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	T 02	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	T 03	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	T 04	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	T 05	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
	T 06	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	T 07	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	T 08	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
	T 09	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
	T 10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	2
	T 11	0	0	0	0	0	0	2	0	0	0	0	0	1	0	0	0	0	0	0	0	3
	T 12	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1
	T 13	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	2
	Total	0	0	0	0	2	0	3	0	1	1	1	0	1	0	1	0	0	0	1	0	11
Over-haul	T 01																					0
	T 02																					0
	T 03																					0
	T 04																					0
	T 05																					1
	T 06																					0
	T 07																					0
	T 08																					1
	T 09																					0
	T 10																					7
	T 11																					1
	T 12																					0
	T 13																					0
	Total																					10

Figure 3.5: Number of tractors used, bought, sold and overhauled per period and tractor type (basic scenario)

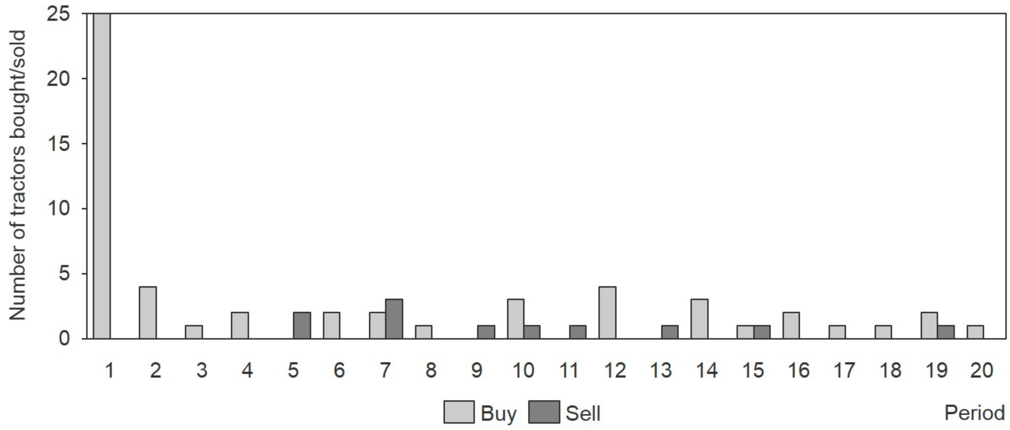

Figure 3.6: Number of tractors bought and sold per period (basic scenario)

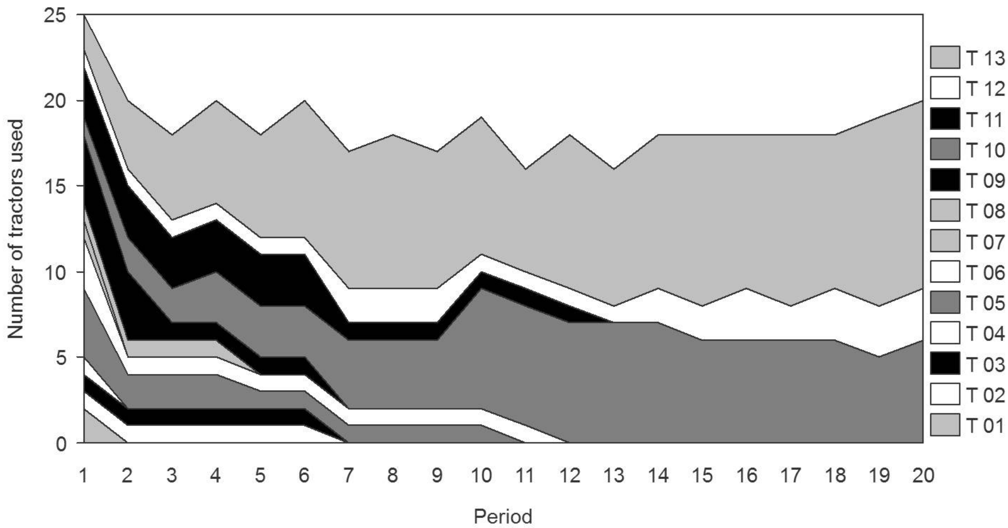

Figure 3.7: Number of tractors used per period and tractor type (basic scenario)

size due to aging, the total fleet size then decreases in periods 2 and 3. As demand increases the fleet size increases again in period 4. Demand with respect to number of jobs is lower in winter than summer (see Table 3.6). However, processing time per job is longer during winter, thus total tractor occupation time is higher during winter. The zig-zag-pattern in periods 4 to 14 (winter 2020) results from this seasonal variation. The fleet size stabilizes after period 14, since I assume one temporal distribution for both

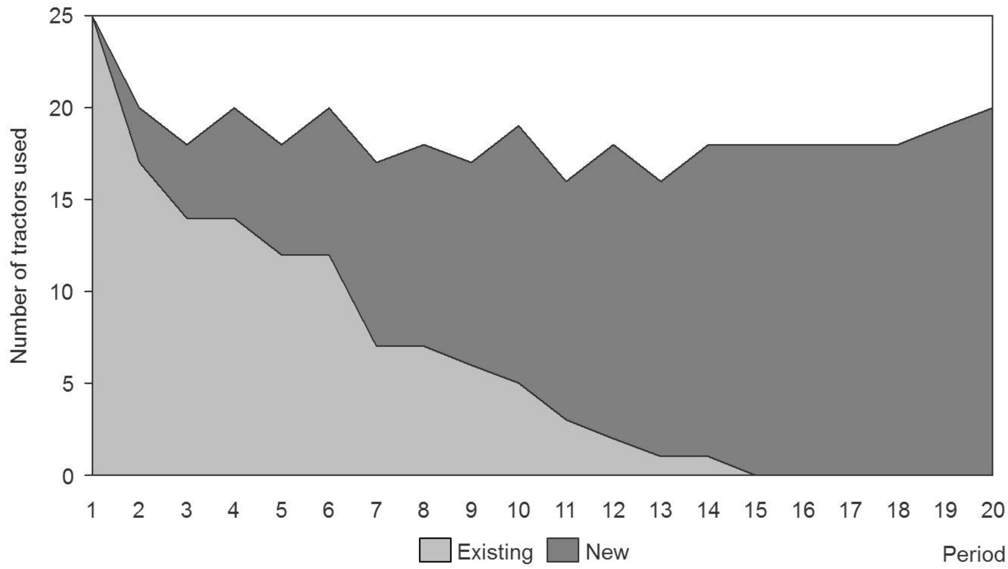

Figure 3.8: Number of tractors used per period and categories of "existing" vs. "new" (basic scenario)

seasons from 2020 onwards.

3.4.2 Demand and risk scenarios

Demand increases with a CAGR of 2% in the basic scenario. Furthermore, an average waiting time of 10 minutes is added to each job based on historical data. Both factors impact the fleet size. I analyze in the following the impact of an increase and a decrease in demand by 10% (scenarios D+10% and D-10%), an increase of the average waiting time to 15 minutes (WT15) and a decrease of the average waiting time to 0 minutes (WT0).

Figure 3.9 compares the waiting time scenarios with the basic scenario. The bars show the total costs TC of the investment plan in percentage of the basic scenario costs (left x-axis). The lines show the number of tractors to be bought, overhauled and sold (right x-axis). Waiting time itself is an indicator of the robustness of an investment plan regarding disruptions in the flight schedule and daily operations. The fleet size decreases considerably when ignoring waiting time (WT0). However, there is a high risk of push-back delays due to flight schedule disruptions. Increasing the average waiting time from 10 minutes to 15 minutes (WT15) creates a greater buffer for disruptions. The comparison of WT0 with the basic scenario can also

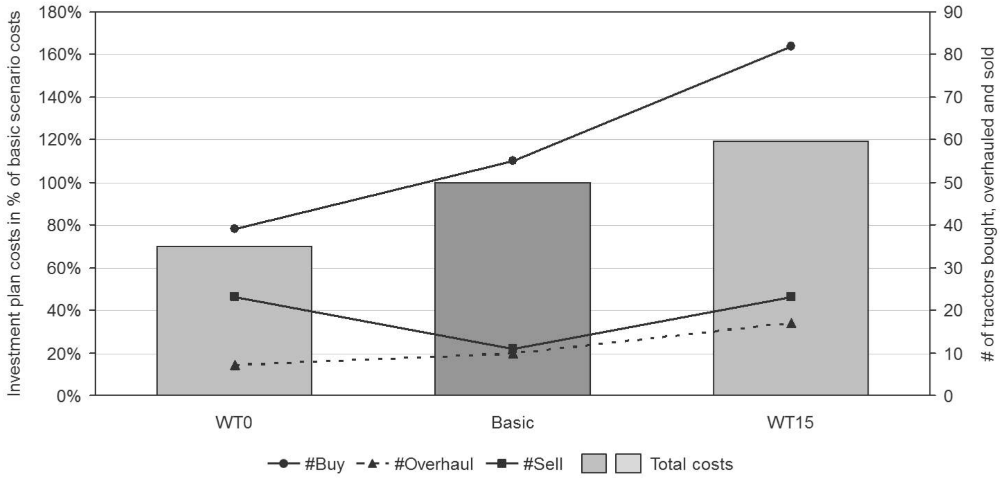

Figure 3.9: Waiting time scenarios vs. basic scenario

be interpreted from the following perspective: Due to disruptions in daily operations, the towing service provider faces about 30% higher investment costs.

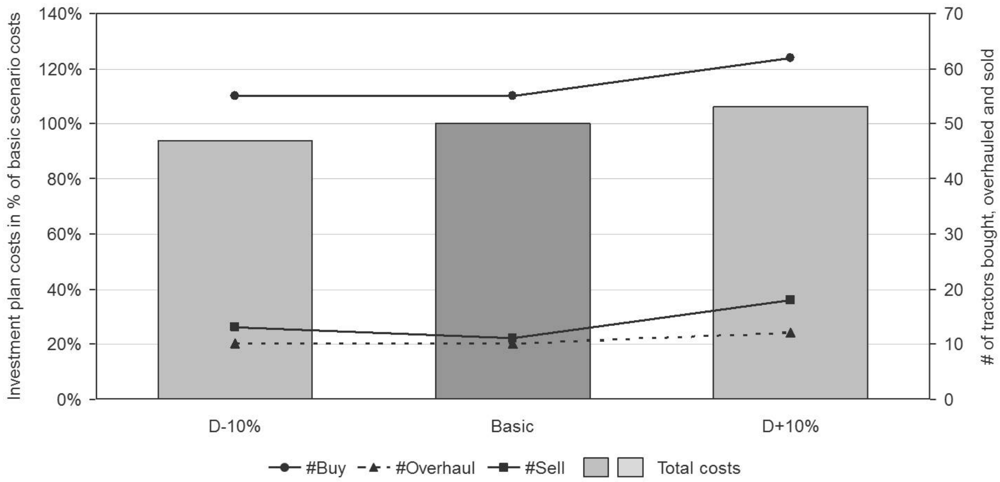

Figure 3.10: Demand scenarios vs. basic scenario

Figure 3.10 shows the results of the demand scenarios. An increase or decrease of demand by 10% is roughly equivalent to a cost increase or decrease of 5%. A demand increase does not expose the towing service provider to any risks, since new tractors can be bought anytime. However, a demand decrease might lead to a suboptimal fleet, if part of the investment plan has already been realized. The greater the differences between the various scenarios, the higher the risk of a suboptimal decision. The later in the planning horizon the differences occur, the higher the chance of revising the investment plan without losing optimality.

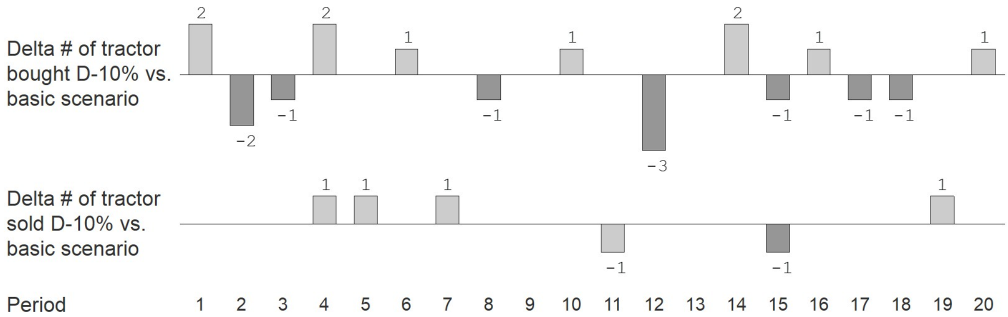

Figure 3.11: Delta of D-10% scenario and basic scenario

Figure 3.11 shows the delta of number of tractors to be bought and sold per period between the D-10% and the basic scenario. A positive number in the chart means more tractors are bought or sold in the D-10% scenario. In total the same number of tractors are bought in both scenarios. Looking at the first 8 periods (i.e. 4 years), the net difference is one additional tractor bought and three additional tractors sold in the D-10% scenario. Buying or selling more tractors if demand does not develop as expected are decision that easily can be carried out. Thus, the investment plan in the case study seems rather robust with respect to demand variations, while waiting time or schedule disruptions have a greater influence on the optimal fleet size.

3.4.3 Cost scenarios

In this section I investigate how the ratio between investment costs and selling prices, and the ratio between investment costs and general overhaul costs influence the investment plan. Moreover, I analyze the impact of utilization rates on the optimal fleet composition.

In the selling price scenarios (S100% - S0%), I vary the revenues for selling tractors. The percentage number in the scenario label indicates the selling price that can be realized on the market in percentage of the initial investment costs. In scenario S100% I assume a tractor can be sold to the market without any loss of value, while scenario S40% assumes a loss of 60% in value if a tractor is sold. Scenario S0% reflects the scenario of not

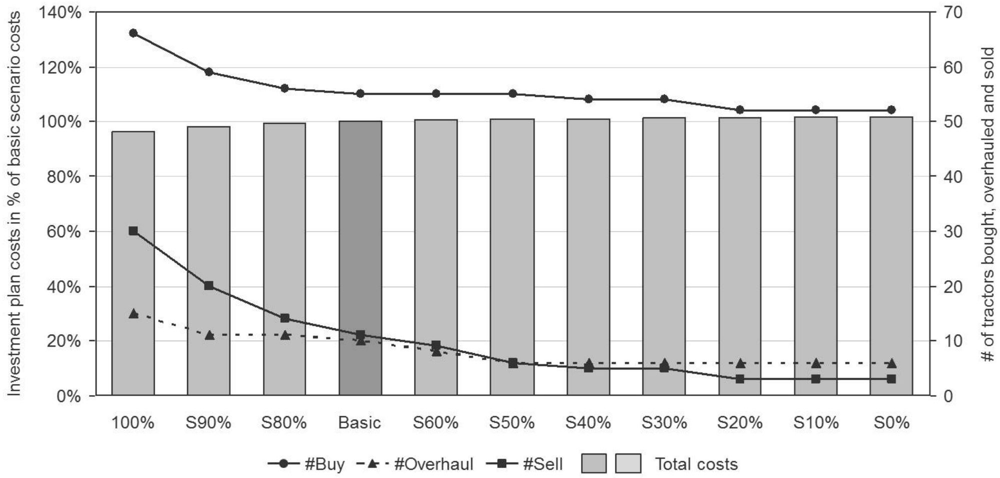

Figure 3.12: Selling price scenarios vs. basic scenario

having a selling option at all. Figure 3.12 summarizes the results for the selling price scenarios. In the basic scenario I assume the selling price equals 70% of the initial investment costs (i.e. a 30% loss of value). Decreasing the selling price has limited impact on the investment plan and costs (see scenarios S60%-S0% in Figure 3.12). Compared to the basic scenario, the total costs increases at most by 2%. In contrast to the negligible changes in scenarios S60%-S0%, an increase in selling prices (scenarios S80%-S100%) does change buying and selling behavior. In scenario S100% in which I assume that tractors can be sold to the market without any loss of value, the number of tractors to be sold triples, and accordingly the number of tractors to be bought increases by almost 30%. Without loss of value when selling a tractor, the fleet more frequently adapts to better fit changing demand.

Analogously to the selling price, I vary the general overhaul costs in scenarios OV-20% - OV+20%. Here the percentage number in the scenario label indicates an increase or reduction of the general overhaul costs compared to the basic scenario. In the basic scenario the general overhaul costs are between 60%-80% of the investment costs for the different tractor types. In scenario OV-10% I decrease the overhaul costs to 50%-70% of the investment costs. The scenario results are displayed in Figure 3.13. As expected, the number of overhauls increases slightly with decreasing overhaul costs, while total costs decrease by up to 4% compared to the basic scenario.

The variable costs per period are determined by the variable costs per

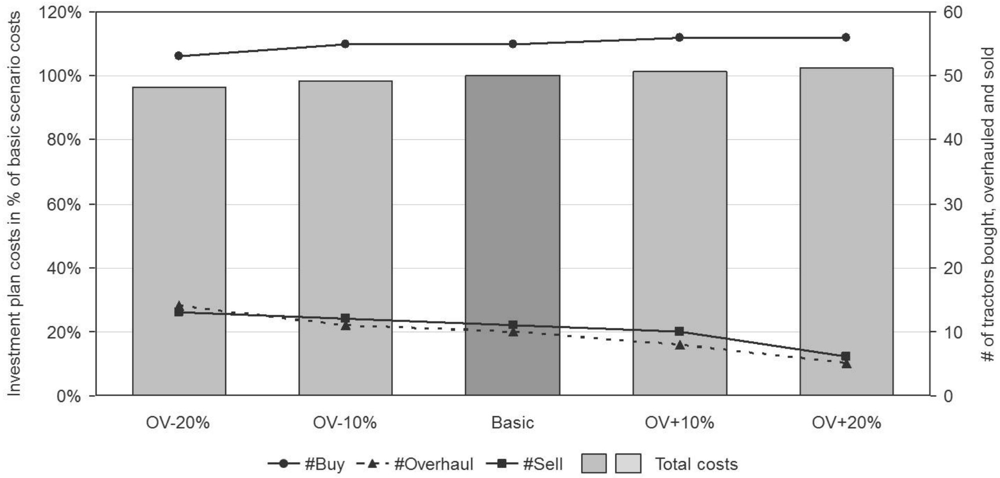

Figure 3.13: Overhaul cost scenarios vs. basic scenario

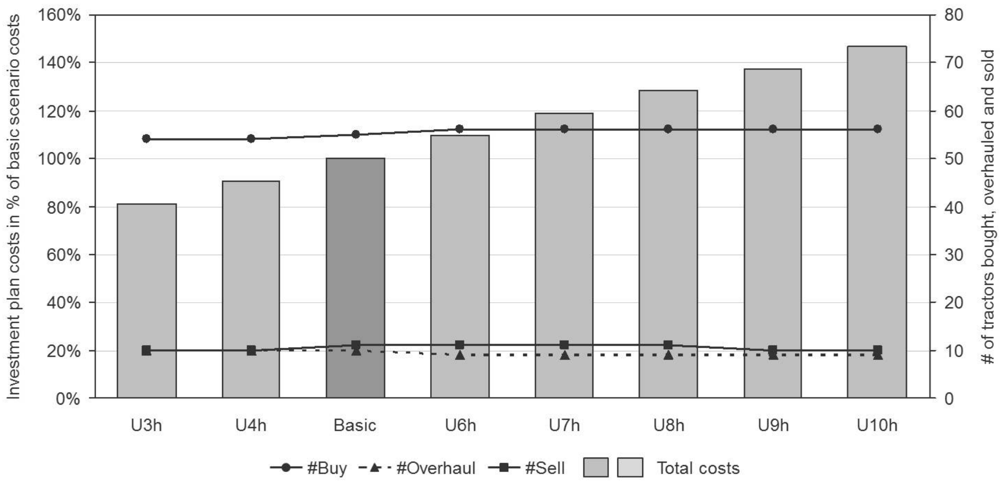

Figure 3.14: Utilization scenarios vs. basic scenario

operating time unit and the utilization time of a tractor. In the basic scenario I assume an average target utilization time of 5 hours per tractor per day. Figure 3.14 shows that an increase (scenarios U6h-U10h) or decrease (scenarios U3h-U4h) of utilization time has little effect on the investment plan itself; it only impacts the total costs. This leads to the conclusion that the assumptions about utilization time is not important for determining the optimal fleet in the case study.

3.4.4 Fleet management scenarios

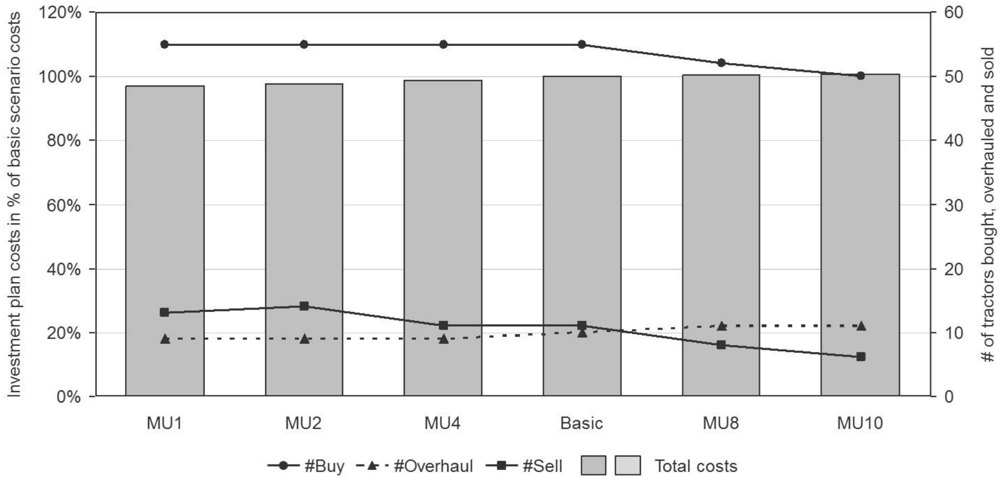

Figure 3.15: Fleet management scenarios vs. basic scenario

In the fleet management scenarios, I investigate the impact of the fleet management policy on the investment plan. The minimum duration of use MU does not reflect a technical feature of a tractor, but rather a management decision. A small MU value allows more flexibility to adjust fleet composition more frequently, while a high MU value results in greater stability in daily operations and less fleet management effort. In the basic scenario the minimum duration of use is set to 6 periods. The scenario analyses show that setting MU to a value of 4, 8 or 10 periods increase or decrease total costs by less than 1% (see Figure 3.15). Further flexibility decreases costs (up to 3% cost reduction in scenario MU1); however, allowing vehicles to be sold after one period does not seem reasonable from a fleet management effort perspective. That is, setting MU to the maximum lifetime of a tractor, i.e. $MU = 10$, is the recommended policy.

3.4.5 Green field scenario

In the green field scenario I ignore the existing fleet and assume the fleet is built from scratch. Compared to the basic scenario, the total costs in the green field scenario decreases by 11% (see Figure 3.16). This equals the savings potential which can be achieved in the long run. Compared to the green field scenario, more tractors are bought in the basic scenario. This

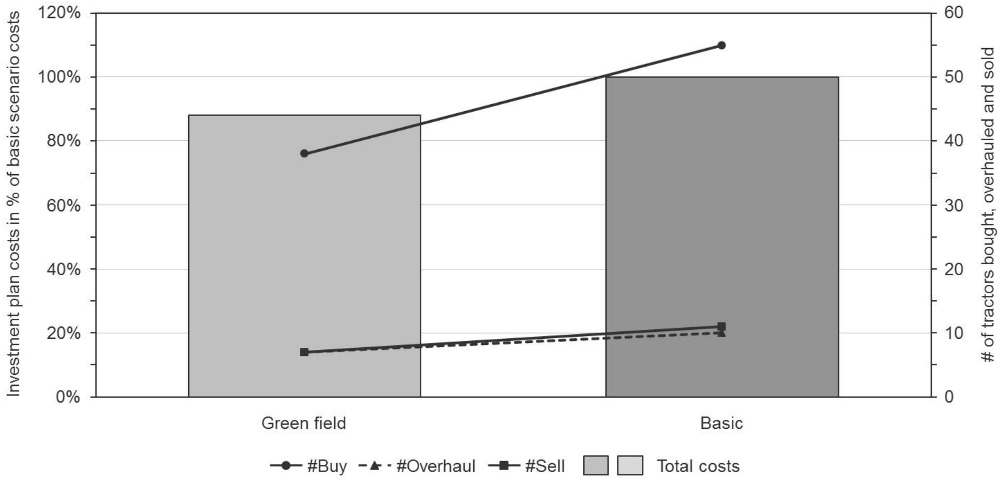

Figure 3.16: Green field scenario vs. basic scenario

can be explained by those tractors in the existing fleet with a remaining lifetime of 1 or 2 periods. Figure 3.17 shows that without an existing fleet, the dominance of tractor types T10, T12 and T13 becomes clear from the first period. In the entire planning horizon, the fleet mix consists of only these three tractor types.

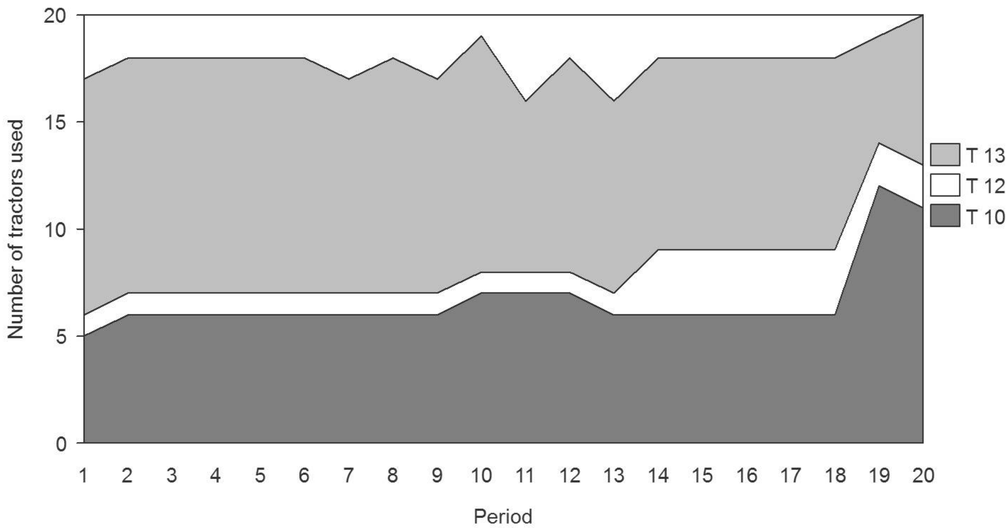

Figure 3.17: Number of tractors used per period and tractor type (green field scenario)

3.5 Summary

In this chapter I address the fleet composition problem of towing tractors at airports at a strategic level. The set-covering formulation derives a multi-period investment plan for set of a heterogeneous towing tractors. The model optimizes fleet size and mix by determining the timing of buying, overhauling and selling tractors. The model takes into account restrictions such as technical compatibility of tractor types with plane types, a minimum and a maximum duration of use. The model incorporates an existing fleet. Period-specific costs in the model factor in assumed cost changes and the discount rate. No literature exists specifically addressing the FCP for towing tractors at airports. The inclusion of the broad spectrum of aspects better captures investment decisions in real-world situations. Furthermore, I introduce a 4-step approach to aggregate demand using flight schedule information. The proposed column generation heuristic solves all 32 scenario instances to optimality with an average runtime of 7 minutes.

I illustrate the application of the model for a major European airport in a case study. Using the model I derive optimal investment plans for a basic scenario and a number of additional scenarios. The scenario analysis results demonstrate the robustness of the investment plan of the basic scenario towards changes in demand, flight disruptions and costs. 11% savings potentials are identified if the model is applied in the long-run.

Chapter 4

Conclusion

This chapter summarizes the implications for towing service providers and the contributions of this work. Furthermore, it outlines potential directions for future research.

4.1 Implications for towing service providers

I applied both proposed models to derive recommendations for the towing service provider in a case study with a major European hub airport. The case study in Chapter 2 leads to insights on main cost drivers and characteristics of efficient schedules. These insights from the comparison of the manual and the optimized schedule can support schedulers in their daily work. In particular, the case study points out the importance of the fleet mix, i.e. which tractors should be used or left in the depot in different periods of the day. Although the average variable costs of the fleet are higher in the optimized schedule than in the manual schedule, the total costs decreased. Compared the the manual assignment, the optimized schedule contains no delays and reduces travel time by more than 30%. The improvements are primarily realized by using the optimal mix of tractors. Thus, the towing service provider should actively manage a driver's tractor choice during the working day.

In Chapter 3, I determine optimal investment plans for various scenarios. The basic scenario reveals an overcapacity of the current fleet and identifies favorable tractor types. Tractor types with low investment and variable costs or flexible compatibility structure predominate the optimal fleet composition in the basic scenario. Further scenario analyses investigate the impact of demand, flight disruptions and costs on the optimal investment strategy. The scenarios show: (i) Compared to disruptions in flight schedules, the impact of demand changes is rather low; (ii) due to flight schedule disruptions towing service providers face 30% higher fleet investment costs; (iii) selling prices and overhaul costs have little influence on the optimal fleet; and (iv) changing tractor utilization increases or decreases operating costs, with limited influence on fleet composition. Overall, the scenario analyses show that the optimal investment plan derived from the model in the case study is robust with respect to changing demand and costs. Finally, I ignore the existing fleet in the green field scenario, i.e. I assume the fleet is being built from scratch. Compared to the basic scenario, which reflects the current situation, the total costs decrease by 11%. This can be interpreted as savings potentials of applying the model in the long-run.

4.2 Contributions of this work

This work optimizes towing processes at airports, as one of the major steps in the ground handling process. I investigate the optimization from an operational and a strategic perspective. Both the scheduling of towing jobs and the towing fleet composition problem have been neglected in the literature thus far. In Chapter 2, I introduce a MIP model based on a vehicle routing formulation. The model incorporates all relevant operational restrictions and specifications of scheduling towing jobs. By combining time windows, mixed fleet, multiple depots and multiple trips in one model, my work contributes to the small number of vehicle routing problem literature in this area. In Chapter 3, I present a set-covering formulation to determine the optimal buy, overhaul and sell policy for a heterogeneous set of towing tractors for a multi-year planning horizon. None of the models in the literature cover all important aspects for deriving an investment strategy for towing tractors in a real-world setting. The model proposed includes restrictions such as a heterogeneous fleet, technical compatibility of tractor types with plane types, a minimum and maximum duration of use, an overhaul and a sell option, as well as a changing fleet composition from period to period. I introduce a column generation based heuristic for solving both models. While applying CPLEX to the original MIP formulations fails to find near optimal solutions at all, the CGH solves all instances of the scheduling model with an optimality gap smaller than 2% and all scenarios of the FCP model optimally. Finally, I derived recommendations for towing service providers based on insights from case studies with a major European hub airport.

4.3 Directions for future research

Future research could be directed at extending the scheduling model to incorporate preferences of airlines for certain tractor types or personnel costs. Also, modifying the scheduling model for an online scheduling application would allow taking into account disruptions in the flight schedules, which are revealed over the course of a day. Thus far the deterministic scheduling model is used to derive insights which are immediately implementable and support schedulers in their future work. However, with minor amendments (for example consideration of the current position of the tractors), the model can be used for an online scheduling approach with periodic scheduling (e.g. every 5 minutes) and a rolling planning horizon (e.g. 60 minutes). From a technical point of view, reformulating the Subproblem (currently the bottleneck in terms of runtime) is a promising research direction. The fleet composition model in Chapter 3 might be adapted to other application areas, such as other vehicles at airports (e.g. de-icing trucks, passenger transport buses, towable passenger boarding stairs), as well as road vehicles (e.g. street buses, trucks). Moreover, the model might be extended by incorporating temporary unavailability of tractors due to maintenance cycles or a general overhaul. Lifetime dependent variable costs might be considered in a model extension.

Appendices

Appendix A

Tractor model - MP and SP

Master problem

Sets:

$\mathcal{B}$	Set of vehicle types
$\mathcal{A}(b)$	Set of routes associated with vehicle type b

Parameters:

$RC_{b,a}$	Costs of route a associated with vehicle type b
CW	Costs associated with auxiliary variable w_i
$Y_{b,a,i}$	1, if route a associated with type b covers plane i, 0 otherwise
NV_b	Number of vehicles of type b

Decision variables:

$\lambda_{b,a}$	1, if route a associated with type b is selected, 0 otherwise
w_i	1, if plane i is not served by selected routes, 0 otherwise

$$\text{Minimize} \sum_{b \in \mathcal{B}} \sum_{a \in \mathcal{A}(b)} RC_{b,a} \cdot \lambda_{b,a} + \sum_{i \in \mathcal{P}} CW \cdot w_i \tag{12a}$$

subject to

$$\sum_{b \in \mathcal{B}} \sum_{a \in \mathcal{A}(b)} Y_{b,a,i} \cdot \lambda_{b,a} + w_i \geq 1 \qquad \forall i \in \mathcal{P} \tag{12b}$$

$$\sum_{a \in \mathcal{A}(b)} \lambda_{b,a} \leq NV_b \qquad \forall b \in \mathcal{B} \tag{12c}$$

$$\lambda_{b,a}; w_i \in \{0,1\} \qquad \forall b \in \mathcal{B}, a \in \mathcal{A}(b); i \in \mathcal{P} \tag{12d}$$

Subproblem(b)

Sets:

$\mathcal{P}$	Set of planes requiring towing
$\mathcal{S}$	Set of depots to start a trip with $\mathcal{S} = \{s_1, ..., s_W\}$, s_1 as central depot
$\mathcal{E}$	Set of depots to end a trip with $\mathcal{E} = \{e_1, ..e_W\}$, e_1 as central depot
$\mathcal{N}$	Set of all nodes with $\mathcal{N} = \{\mathcal{P} \cup \mathcal{S} \cup \mathcal{E}\}$
$\mathcal{R}$	Set of trips a tractor has to drive

Parameters:

δ_i	Dual value of demand constraint of plane i in MP
μ_b	Dual value of convexity constraint b in MP
VC	Variable costs per operating time unit
DC	Delay costs per time unit
SD_i	Service duration to serve plane i or resting time at ending depot node i
$TT_{i,j}$	Travel time to drive from plane i to plane j
CP_i	1, if tractor type b is compatible with plane i, 0 otherwise
ET_i	Earliest time to start service at node i
LT_i	Latest time to start service at node i
$D^{\max}$	Maximum delay per job
T^{max}	Maximum duration of one trip (time between leaving and returning to depot)
$M_{i,j}$	Parameter specific big M with $(M_{i,j} \geq LT_i + D_{\max} + SD_i + TT_{i,j} - ET_j)$

Functions:

$f(e)$	Maps ending depot to starting depot of same depot w (e.g. $f(e_1) = s_1$, $f(e_2) = s_2$)

Decision variables:

y_i	1 if plane i served, 0 otherwise
$x_{i,j}$	1, if tractor visits node j immediately after having visited node i, 0, otherwise
b_i	beginning time to serve node i
d_i	delay of service at plane i (compared to LT_i)

$$
\begin{aligned}
\text{Minimize } & \sum_{r\in\mathcal{R}}\sum_{i,j\in\mathcal{N}} VC\cdot TT_{i,j}\cdot x_{r,i,j} \\
& +\sum_{r\in\mathcal{R}}\sum_{i\in\mathcal{P}}\sum_{j\in\mathcal{N}} VC\cdot SD_i\cdot x_{r,i,j} + DC\cdot\sum_{i\in\mathcal{P}} d_i \\
& -\left(\sum_{i\in\mathcal{P}}\delta_i\cdot y_i+\mu_b\right) \qquad (13a)
\end{aligned}
$$

subject to

$$\sum_{r\in\mathcal{R}}\sum_{j\in\mathcal{N}} x_{r,i,j}-y_i=0 \qquad \forall i\in\mathcal{P} \qquad (13b)$$

$$CP_{b,i}\le y_{b,i} \qquad \forall i\in\mathcal{P} \qquad (13c)$$

$$\sum_{j\in\mathcal{P}\cup\mathcal{E}} x_{1,s_1,j}=1 \qquad (13d)$$

$$\sum_{i\in\mathcal{P}\cup\mathcal{S}} x_{R,i,e_1}=1 \qquad (13e)$$

$$\sum_{s\in\mathcal{S}}\sum_{j\in\mathcal{P}\cup\mathcal{E}} x_{r,s,j}=1 \qquad \forall r=2..R \qquad (13f)$$

$$\sum_{i\in\mathcal{P}\cup\mathcal{S}}\sum_{e\in\mathcal{E}} x_{r,i,e}=1 \qquad \forall r=1..(R-1) \qquad (13g)$$

$$\sum_{i\in\mathcal{P}\cup\mathcal{S}} x_{r,i,e}-\sum_{j\in\mathcal{P}\cup\mathcal{E}} x_{r,f(e),j}=0 \qquad \forall r=1..(R-1),\ e\in\mathcal{E} \qquad (13h)$$

$$\sum_{i\in\mathcal{P}} x_{r,i,h}-\sum_{j\in\mathcal{P}} x_{r,h,j}=0 \qquad \forall r\in\mathcal{R},\ h\in\mathcal{P} \qquad (13i)$$

$$b_{r,e}-M_{i,j}\cdot\sum_{i\in\mathcal{P}\cup\mathcal{S}} x_{r,i,e}\le 0 \qquad \forall r\in\mathcal{R},\ e\in\mathcal{E} \qquad (13j)$$

$$b_{r,s}-M_{i,j}\cdot\sum_{j\in\mathcal{P}\cup\mathcal{E}} x_{r,s,j}\le 0 \qquad \forall r\in\mathcal{R},\ s\in\mathcal{S} \qquad (13k)$$

$$\sum_{e\in\mathcal{E}} b_{r,e}\le\sum_{s\in\mathcal{S}} b_{r,s} \qquad \forall r=1..(R-1) \qquad (13l)$$

$$ET_i\cdot\sum_{j\in\mathcal{P}\cup\mathcal{E}} x_{r,i,j}\le b_{r,i} \qquad \forall r\in\mathcal{R},\ i\in\mathcal{P} \qquad (13m)$$

$$
\begin{aligned}
& b_{r,i} + SD_i + TT_{r,i,j} && \\
& \leq b_{r,j} + M_{i,j} \cdot (1 - x_{r,i,j}) && \forall r \in \mathcal{R},\ i,j \in \mathcal{N} && \text{(13n)} \\
& \sum_{r \in \mathcal{R}} b_{r,i} - LT_i \leq d_i && \forall i \in \mathcal{P} && \text{(13o)} \\
& \sum_{e \in \mathcal{E}} b_{r,e} - \sum_{s \in \mathcal{S}} b_{r,s} \leq T^{max} && \forall r \in \mathcal{R} && \text{(13p)} \\
& x_{r,i,j} \in \{0;1\} && \forall r \in \mathcal{R},\ i,j \in \mathcal{N} && \text{(13q)} \\
& b_i \geq 0 && \forall i \in \mathcal{N} && \text{(13r)} \\
& y_i \in \{0;1\} && \forall i \in \mathcal{P} && \text{(13s)} \\
& 0 \leq d_i \leq D^{\max} && \forall i \in \mathcal{P} && \text{(13t)}
\end{aligned}
$$

Appendix B

Computational test results - CGH depot model vs. CGH tractor model

Prob	# Pln	# Dpt	# Trp	T^{max}	# Trctr	CGH depot model IP Val	Gap* %	LP Relax	Time Sec	CGH tractor model IP Val	Gap* %	LP Relax	Time Sec
3	10	1	1	60	23	702	0.0	702	4	702	0.0	702	9
2	10	1	2	60	23	702	0.0	702	5	702	0.0	702	11
1	10	2	2	60	23	672	0.0	672	13	672	0.0	672	22
6	25	1	1	60	23	1,505	0.0	1,505	47	1,501	0.0	1,505	53
5	25	1	2	60	23	1,618	0.0	1,618	3,376	1,620	0.0	1,618	9,832
4	25	2	2	60	23	1,500	0.0	1,500	5,637	1,500	0.0	1,500	25,732

*Gap=(IP Value - LP Relax) / IP Value · 100

Table B.1: Computational test results CGH depot model vs. CGH tractor model - Heterogeneous fleet of 23 tractors and 12 types, 10/25 planes

Appendix C

Fleet composition model - MIP

Sets:

$\mathcal{V}$	Set of tractors
$\mathcal{D}$	Set of demand patterns (index d)
$\mathcal{T}$	Set of periods (index t)

Parameters:

$VC_{v,t}$	Variable costs of tractor v in period t
$IC_{v,t}$	Investment costs of tractor v in period t
$OC_{v,t}$	General overhaul costs of tractor v in period t
$SR_{v,t}$	Sales revenue for one remaining usage period, if tractor v is sold in period t
$CP_{v,d}$	1, if tractor v is compatible with at least one plane type associated with demand pattern d, 0 otherwise
DU_v	Maximum duration of use of tractor v without general overhaul
AD_v	Maximum additional duration of use of tractor v after a general overhaul
MU_v	Minimum duration of use after a general overhaul before tractor v can be sold
$DM_{d,t}$	Demand of demand pattern d in period t

Variables:

$x_{v,t}$	1, if tractor is used in period t, 0 otherwise
$y_{v,t}^{\text{buy}}$	1, if tractor v is bought in period t, 0 otherwise
y_v^{ov}	1, if tractor v is overhauled, 0 otherwise

$y^{\text{sell}}_{v,t}$	1, if tractors v is sold in period t, 0 otherwise
$u_{v,t,\tilde{t}}$	Remaining lifetime if tractor v is bought in period t
$o^{\text{cost}}_{v,t}$	Costs of general overhaul if tractor v is bought in period t and sold in period $\tilde{t}$

$$\begin{aligned}\text{Minimize} \sum_{v\in\mathcal{V}}\sum_{t\in\mathcal{T}} VC_{v,t}\cdot x_{v,t} + \sum_{v\in\mathcal{V}}\sum_{t\in\mathcal{T}} IC_{v,t}\cdot y^{\text{buy}}_{v,t} \\ + \sum_{v\in\mathcal{V}}\sum_{t\in\mathcal{T}} o^{\text{cost}}_{v,t} - \sum_{v\in\mathcal{V}}\sum_{t\in\mathcal{T}}\sum_{\tilde{t}\in\mathcal{T}} SR_{v,\tilde{t}}\cdot u_{v,t,\tilde{t}}\end{aligned} \tag{14a}$$

subject to

$$x_{v,t-1} + y^{\text{buy}}_{v,t} \leq 1 \qquad \forall v\in\mathcal{V}, t\in\mathcal{T} \tag{14b}$$

$$x_{v,t} - x_{v,p-1} - y^{\text{buy}}_{v,p} \leq 0 \qquad \forall v\in\mathcal{V}, t\in\mathcal{T} \tag{14c}$$

$$-x_{v,t-1} + y^{\text{sell}}_{v,t} \leq 0 \qquad \forall v\in\mathcal{V}, t\in\mathcal{T} \tag{14d}$$

$$x_{v,t} + y^{\text{sell}}_{v,t} \leq 1 \qquad \forall v\in\mathcal{V}, t\in\mathcal{T} \tag{14e}$$

$$-x_{v,t} + x_{v,t-1} - y^{\text{sell}}_{v,t} \leq 0 \qquad \forall v\in\mathcal{V}, t\in\mathcal{T} \tag{14f}$$

$$y^{\text{ov}}_{v} \leq \sum_{t\in\mathcal{T}} y^{\text{buy}}_{v,t} \qquad \forall v\in\mathcal{V} \tag{14g}$$

$$\begin{aligned}&\sum_{\tilde{t}\in\mathcal{T}} \tilde{t}\cdot y^{\text{sell}}_{v,\tilde{t}} - \sum_{t\in\mathcal{T}} t\cdot y^{\text{buy}}_{v,t} \\ &\geq (DU_v+1)\cdot y^{\text{ov}}_{v} \qquad \forall v\in\mathcal{V}\end{aligned} \tag{14h}$$

$$\begin{aligned}&o^{\text{cost}}_{v,t} \geq OC_{v,t+DU_v}\cdot \\ &\qquad (y^{\text{buy}}_{v,t} + y^{\text{ov}}_{v} - 1) \qquad \forall v\in\mathcal{V}, \forall t\in\{1,...,|\mathcal{T}|-DU_v\}\end{aligned} \tag{14i}$$

$$u_{v,t,\tilde{t}} \leq (DU_v + AD_v)\cdot y^{\text{buy}}_{v,t} \qquad \forall v\in\mathcal{V}, t,\tilde{t}\in\mathcal{T} \tag{14j}$$

$$u_{v,t,\tilde{t}} \leq (DU_v + AD_v)\cdot y^{\text{sell}}_{v,\tilde{t}} \qquad \forall v\in\mathcal{V}, t,\tilde{t}\in\mathcal{T} \tag{14k}$$

$$\begin{aligned}u_{v,t,\tilde{t}} \leq\ & AD_v\cdot y^{\text{ov}}_{v} + DU_v \\ & - (\tilde{t}\cdot y^{\text{sell}}_{v,\tilde{t}} - t\cdot y^{\text{buy}}_{v,t}) \\ & + \tilde{t}\cdot(1-y^{\text{buy}}_{v,t}) \qquad \forall v\in\mathcal{V}, t,\tilde{t}\in\mathcal{T}\end{aligned} \tag{14l}$$

$$\sum_{t\in\mathcal{T}} y^{\text{buy}}_{v,t} \leq 1 \qquad \forall v\in\mathcal{V} \tag{14m}$$

$$\begin{aligned}x_{v,\tilde{t}} \geq y^{\text{buy}}_{v,t} \qquad & \forall v\in\mathcal{V}, t\in\{1,...,|\mathcal{T}|-1\}, \tilde{t}\in \\ & \{t,...,min\{t+MU_v-1,|\mathcal{T}|-1\}\}\end{aligned} \tag{14n}$$

$$1 - x_{v,t+DU_v+AD_v} \geq y_v^{\text{oh}} + y_{v,t}^{buy} - 1 \quad \forall v \in \mathcal{V}, \; t \in \{1, ..., |\mathcal{T}| - 1 - AD_v - DU_v\} \tag{14o}$$

$$1 - x_{v,t+DU_v} \geq y_{v,t}^{\text{buy}} - y_v^{\text{oh}} \quad \forall v \in \mathcal{V}, t \in \{1, ..., |\mathcal{T}| - 1 - DU_v\} \tag{14p}$$

$$\sum_{v \in \mathcal{V}} CP_{v,d} \cdot x_{v,t} \geq DM_{d,t} \quad \forall d \in \mathcal{D}, t \in \mathcal{T} \tag{14q}$$

$$x_{v,t}, y_{v,t}^{\text{buy}}, y_v^{\text{ov}}, y_{v,t}^{\text{sell}} \in \{0; 1\} \quad \forall v \in \mathcal{V}, t \in \mathcal{T} \tag{14r}$$

$$o_{v,t}^{\text{cost}}, u_{v,t,\tilde{t}} \geq 0 \quad \forall v \in \mathcal{V}, t, \tilde{t} \in \mathcal{T} \tag{14s}$$

Appendix D

Abbreviations and notations

D.1 General abbreviations

# Dpt	Number of depots
# PLN	Number of planes
# Trctr	Number of tractors
# Trp	Number of trips
CAGR	Compounded Annual Growth Rate
CG	Column Generation
CGH	Column Generation Heuristic
FCP	Fleet Composition Problem
FSMVRP	Fleet Size and Mix Vehicle Routing Problem
FSP	Fleet Sizing Problem
GRASP	Greedy Randomized Adaptive Search Procedures
HVRP	Heterogeneous fleet Vehicle Routing Problem

IP	Integer Program
LP	Linear Program
LP Relax	LP Relaxation
MDVRP	Multiple Depot Vehicle Routing Problem
MIP	Mixed Integer Program
MP	Master Problem
mTSP	multiple Traveling Salesman Problem
MTVRP	Multiple Trip Vehicle Routing Problem
NP-hard	Non-deterministic Polynomial-time hard
RMP	Restricted Master Problem
Sec	Seconds
SP	Subproblem
VRP	Vehicle Routing Problem
VRPTW	Vehicle Routing Problem with Time Window

D.2 Notations depot model - MIP

Sets:

$\mathcal{E}_r$	Set of depots where the r-th trip can be ended,
	with $\mathcal{E} = \mathcal{E}_1 \cup \mathcal{E}_2 \cup ... \cup \mathcal{E}_{R^{max}}$
$\mathcal{N}$	Set of all nodes with $\mathcal{N} = \{\mathcal{P} \cup \mathcal{S} \cup \mathcal{E}\}$
$\mathcal{P}$	Set of planes requiring towing
$\mathcal{S}_r$	Set of depots where the r-th trip can be started,
	with $\mathcal{S} = \mathcal{S}_1 \cup \mathcal{S}_2 \cup ... \cup \mathcal{S}_{R^{mmax}}$
$\mathcal{V}$	Set of vehicles

Parameters:

$CP_{v,i}$	1, if tractor v is compatible with plane i, 0 otherwise
$D^{\max}$	Maximum delay per job
DC	Delay costs per time unit
ET_i	Earliest time to start service at node i
LT_i	Latest time to start service at node i
$M_{v,i,j}$	Parameter specific big M with
	$(M_{v,i,j} \geq LT_i + D_{\max} + SD_i + TT_{v,i,j} - ET_j)$
$R^{\max}$	Number of trips per vehicle
SD_i	Service duration to serve plane i
	or resting time at ending depot node i
$T^{\max}$	Maximum duration of one trip
$TT_{v,i,j}$	Travel time of tractor v to drive from node i to node j
VC_v	Variable costs of vehicle v per operating time unit

Functions:

$ED(i)$	Maps starting depot i to the ending depot of the directly preceding trip
$SD(i)$	Maps ending depot i to each potential starting depot of the same trip

Variables:

$b_{v,i}$	beginning time of tractor v to serve node i
d_i	delay of service at plane i (compared to LT_i)
$x_{v,i,j}$	1, if tractor v visits node j immediately after having visited node i, 0 otherwise

D.3 Notations tractor model - MIP

Sets:

$\mathcal{E}$	Set of depots to end a trip with $\mathcal{E} = \{e_1, ..e_W\}$, e_1 as central depot
$\mathcal{N}$	Set of all nodes with $\mathcal{N} = \{\mathcal{P} \cup \mathcal{S} \cup \mathcal{E}\}$
$\mathcal{P}$	Set of planes requiring towing
$\mathcal{S}$	Set of depots to start a trip with $\mathcal{S} = \{s_1, ..., s_W\}$, s_1 as central depot
$\mathcal{V}$	Set of vehicles (tractors), with $\mathcal{V} = \{\mathcal{V}_1 \cup, ..., \cup \mathcal{V}_R\}$
$\mathcal{V}_r$	Set of vehicles for r-th trip

Parameters:

$CP_{v,i}$	1, if tractor v is compatible with plane i, 0 otherwise
$D^{\max}$	Maximum delay per job
DC	Delay costs per time unit
ET_i	Earliest time to start service at node i
LT_i	Latest time to start service at node i
$M_{v,i,j}$	Parameter specific big M with
	$(M_{v,i,j} \geq LT_i + D_{\max} + SD_i + TT_{v,i,j} - ET_j)$
SD_i	Service duration to serve plane i
	or resting time at ending depot node i
T^{max}	Maximum duration of one trip
	(time between leaving and returning to depot)
$TT_{v,i,j}$	Travel time of tractor v to drive from plane i to plane j
VC_v	Variable costs of tractor per operating time unit
Z	Number of actual vehicles with $Z =\mid \mathcal{V}_r \mid$

Functions:

$f(e)$	Maps ending depot to starting depot
	of same depot w (e.g. $f(e_1) = s_1$, $f(e_2) = s_2$)

Variables:

$b_{v,i}$	beginning time of tractor v to serve node i
d_i	delay of service at plane i (compared to LT_i)
$x_{v,i,j}$	1, if tractor v visits node j immediately after
	having visited node i, 0 otherwise

D.4 Notations depot model - MP and SP

Sets:

$\mathcal{A}(b)$	Set of routes associated with vehicle type b
$\mathcal{B}$	Set of vehicle types
$\mathcal{E}_r$	Set of depots where the r-th trip can be ended, with $\mathcal{E} = \mathcal{E}_1 \cup \mathcal{E}_2 \cup ... \cup \mathcal{E}_{R^{max}}$
$\mathcal{N}$	Set of all nodes with $\mathcal{N} = \{\mathcal{P} \cup \mathcal{S} \cup \mathcal{E}\}$
$\mathcal{P}$	Set of planes requiring towing
$\mathcal{S}_r$	Set of depots where the r-th trip can be started, with $\mathcal{S} = \mathcal{S}_1 \cup \mathcal{S}_2 \cup ... \cup \mathcal{S}_{R^{max}}$

Parameters:

δ_i	Dual value of demand constraint of plane i in MP
μ_b	Dual value of convexity constraint b in MP
$CP_{b,i}$	1, if tractor type b is compatible with plane i, 0 otherwise
CW	Costs associated with auxiliary variable w_i
$D^{\max}$	Maximum delay per job
DC	Delay costs per time unit
ET_i	Earliest time to start service at node i
LT_i	Latest time to start service at node i
$M_{i,j}$	Parameter specific big M with $(M_{i,j} \geq LT_i + D_{\max} + SD_i + TT_{i,j} - ET_j)$
NV_b	Number of vehicles of type b
$R^{\max}$	Number of trips per vehicle

$RC_{b,a}$	Costs of route a associated with vehicle type b
SD_i	Service duration to serve plane i
	or resting time at ending depot node i
$T^{\max}$	Maximum duration of one trip
$TT_{i,j}$	Travel time to drive from node i to node j
VC	Variable costs per operating time unit
$Y_{b,a,i}$	1, if route a associated with type b
	covers plane i, 0 otherwise

Functions:

$ED(i)$	Maps starting depot i to
	the ending depot of the directly preceding trip
$SD(i)$	Maps ending depot i to
	each potential starting depot of the same trip

Variables:

$\lambda_{b,a}$	1, if route a associated with type b is selected, 0 otherwise
w_i	1, if plane i is not served by selected routes, 0 otherwise
$x_{i,j}$	1, if tractor visits node j immediately after
	having visited node i, 0 otherwise
b_i	beginning time of service at node i
d_i	delay of service at plane i (compared to LT_i)
y_i	1 if plane i served, 0 otherwise

D.5 Notations fleet composition model - MP and SP

Sets:

$\mathcal{A}(b)$	Set of investment plans associated with tractor type b
$\mathcal{B}$	Set of tractor types
D	Set of demand patterns (index d)
T	Set of periods (index t)

Parameters:

δ_d, t	Dual value of demand pattern d in period t in MP
$\tilde{\delta}_b$	Dual value of existing fleet constraint b in MP
AD	Maximum additional duration of use after a general overhaul
CW	Costs associated with auxiliary variable w_i
$CP_{b,d}$	1, if tractor type b is compatible with at least one plane type associated with demand pattern d, 0 otherwise
$DM_{d,t}$	Demand of demand pattern d in period t
DU	Maximum duration of use without general overhaul (in periods)
$TC_{b,a}$	Costs of investment plan a associated with tractor type b
IC_t	Investment costs in period t
MU	Minimum duration of use before tractor can be sold (in periods)

NE_b	Number of existing tractors of tractor type b
OC_t	General overhaul costs in period t
SR_t	Selling price for one remaining usage period, if tractor is sold in period t
$X_{b,a,t}$	1, if (dis-)investment plan a for tractor type b covers period t, 0 otherwise
VC_t	Variable costs in period t

Variables:

$\lambda_{b,a}$	Number of tractors of type b bought and sold according to (dis-)investment plan a
$u_{t,\tilde{t}}$	Remaining lifetime if tractor is bought in period t and sold in period $\tilde{t}$
$w_{d,t}$	Number of external tractors to cover demand pattern d in period t
x_t	1, if tractor is used in period t, 0 otherwise
y_t^{buy}	1, if tractor is bought in period t, 0 otherwise
y^{ov}	1, if tractor is overhauled, 0 otherwise
y_t^{sell}	1, if tractors is sold in period t, 0 otherwise
o_t^{cost}	Costs of general overhaul if tractor is bought in period t

Bibliography

[1] Airbus S.A.S., Global market forecast 2012-2031, Technical report, 2012.

[2] Airport Authority Zürich Airport, Operational towing survey, Technical report, Zürich, 1992.

[3] Alsbury, P., The vehicle fleet mix, *International Journal of Physical Distribution & Logistics Management*, 2(3):123–125, 1972.

[4] Andersson, K., F. Carr, E. Feron, and W. D. Hall, Analysis and Modeling of Ground Operations at Hub Airports, in *3rd USA/Europe Air Traffic Management R&D Seminar*, June, Napoli, 2000.

[5] Atkin, J. A. D., E. K. Burke, and J. S. Greenwood, A comparison of two methods for reducing take-off delay at London Heathrow airport, *Journal of Scheduling*, 14(5):409–421, 2011.

[6] Atkin, J. A. D., G. De Maere, E. K. Burke, and J. S. Greenwood, Addressing the Pushback Time Allocation Problem at Heathrow Airport, *Transportation Science*, 47(4):584–602, 2012.

[7] Azi, N., M. Gendreau, and J.-Y. Potvin, An exact algorithm for a single-vehicle routing problem with time windows and multiple routes, *European Journal of Operational Research*, 178(3):755–766, 2007.

[8] Azi, N., M. Gendreau, and J.-Y. Potvin, An exact algorithm for a vehicle routing problem with time windows and multiple use of vehicles, *European Journal of Operational Research*, 202(3):756–763, 2010.

[9] Balakrishnan, H. and Y. Jung, A framework for coordinated surface operations planning at dallas-fort worth international airport, in *Proceedings of the AIAA Guidance, Navigation, and Control Conference*, USA, 2007.

[10] Baldacci, R., A. Mingozzi, and R. Roberti, Recent exact algorithms for solving the vehicle routing problem under capacity and time window constraints, *European Journal Of Operational Research*, 218(1):1–6, 2011.

[11] Barnhart, C., E. L. Johnson, G. L. Nemhauser, M. W. P. Savelsbergh, and P. H. Vance, Branch-and-price: Column generation for solving huge integer programs, *Operations Research*, 46(3):16–329, 1998.

[12] Bektas, T., The multiple traveling salesman problem: an overview of formulations and solution procedures, *Omega*, 34(3):209 – 219, 2006.

[13] Bielli, M., A. Bielli, and R. Rossi, Trends in Models and Algorithms for Fleet Management, *Procedia - Social and Behavioral Sciences*, 20:4–18, 2011.

[14] Boeing Commercial Airplanes, Current Market Outlook 2012-2031, Technical report, 2012.

[15] Bramel, J. and D. Simchi-Levi, On the effectiveness of set covering formulations for the vehicle routing problem with time windows, *Operations Research*, 45(2):295–301, 1997.

[16] Burt, C., L. Caccetta, P. Welgama, and L. Fouché, Equipment selection with heterogeneous fleets for multiple-period schedules, *Journal of the Operational Research Society*, 62(8):1498–1509, 2011.

[17] Carr, F., G. Theis, and J. Clarke, Evaluation of improved pushback forecasts derived from airline ground operations data, *Journal of Aerospace Computing*, 2(1):25–43, 2005.

[18] Ceselli, A., G. Righini, and M. Salani, A column generation algorithm for a rich vehicle-routing problem, *Transportation Science*, 43(1):56–69, 2009.

[19] Cheng, Y., Solving push-out conflicts in apron taxiways of airports by a network-based simulation, *Computers & Industrial Engineering*, 34(2):351–369, 1998.

[20] Cornillier, F., F. Boctor, and J. Renaud, Heuristics for the multi-depot petrol station replenishment problem with time windows, *European Journal of Operational Research*, 220(2):361–369, 2012.

[21] Couillard, J. and A. Martel, Vehicle fleet planning the road transportation industry, *IEEE Transactions on Engineering Management*, 37(1):31–36, 1990.

[22] Dantzig, G. and J. Ramser, The truck dispatching problem, *Management Science*, 6(1):80–91, 1959.

[23] Dantzig, G. B. and P. Wolfe, Decomposition principle for linear programs, *Operations Research*, 8(1):101–111, 1960.

[24] Desaulniers, G., J. Desrosiers, and M. M. Solomon, *Column generation*, Springer, New York, 2005.

[25] Desrochers, M., J. Desrosiers, and M. Solomon, A new optimization algorithm for the vehicle routing problem with time window, *Operations Research*, 40(2):342–354, 1992.

[26] Desrochers, M., J. Lenstra, and M. Savelsbergh, A classification scheme for vehicle routing and scheduling problems, *European Journal of Operational Reserach*, 46(3):322–332, 1990.

[27] Deutsche Lufthansa AG, Towing with 1,360 horsepower - 560 tonnes carried piggy-back, http://a380.lufthansa.com/fascination/#/de/en/main/faszination_fliegen/flughafen/pushback/p1, viewed September 23, 2012.

[28] Dondo, R. and J. Cerda, A cluster-based optimization approach for the multi-depot heterogeneous fleet vehicle routing problem with time windows, *European Journal of Operational Research*, 176(3):1478–1507, 2007.

[29] Du, J., J. O. Brunner, and R. Kolisch, Obtaining the optimal fleet mix - a case study about towing tractors at airports, Working Paper, TUM School of Management, Technische Universität München, 2013.

[30] Du, J., J. O. Brunner, and R. Kolisch, Planning towing processes at airports more efficiently, Working Paper, TUM School of Management, Technische Universität München, 2013.

[31] Eksioglu, B., A. V. Vural, and A. Reisman, The vehicle routing problem: A taxonomic review, *Computers & Industrial Engineering*, 57(4):1472–1483, 2009.

[32] Etezadi, T. and J. Beasley, Vehicle fleet composition, *Journal of the Operational Research Society*, 34(1):87–91, 1983.

[33] EUROCONTROL, Performance Review Report. An Assessment of Air Traffic Management in Europe during the Calendar Year 2011, 2012.

[34] EUROCONTROL, Challenges of Growth 2013, Task 4: European Air Traffic in 2035, 2013.

[35] Golden, B. L., S. Raghavan, and E. A. Wasil, *The vehicle routing problem: Latest advances and new challenges*, Springer, New York, 2008.

[36] Goldhofer AG, Flugzeugschlepper AST-1 X, http://goldhofer.de/gh-de/airport-technologie/flugzeugschlepper-ast-1.php?WSESSIONID=1ca75ceb20c43146d4f16869431674a5, viewed September 23, 2012.

[37] Gould, J., The size and composition of a road transport fleet, *Operational Research Quarterly*, 20(1):81–92, 1969.

[38] Hoff, A., H. Andersson, M. Christiansen, G. Hasle, and A. Lokketangen, Industrial aspects and literature survey: Fleet composition and routing, *Computers & Operations Research*, 37(12):2041–2061, 2010.

[39] Imai, A. and F. Rivera, Strategic fleet size planning for maritime refrigerated containers, *Maritime Policy & Management*, 28(4):361–374, 2001.

[40] Kazda, A. and R. E. Caves, *Airport design and operation*, Elsevier, Oxford UK, 2007.

[41] Keith, G. and A. Richards, Optimization of taxiway routing and runway scheduling, in *Proceedings of the AIAA Guidance, Navigation and Control Conference, USA*, 2008.

[42] Kirby, D., Is Your Fleet the Right Size, *Journal of the Operational Research Society*, 10:252, 1959.

[43] Kuhn, K. and S. Loth, Airport Service Vehicle Scheduling, in *8th USA/Europe Air Traffic Management Research and Development Seminar*, USA, 2009.

[44] Laporte, G., Fifty years of vehicle routing, *Transportation Science*, 43(4):408–416, 2009.

[45] Lee, H., I. Simaiakis, and H. Balakrishnan, A comparison of aircraft trajectory-based and aggregate queue-based control of airport taxi processes, in *Digital Avionics Systems Conference (DASC), 2010 IEEE/AIAA 29th*, pages 1.B.3–1 – 1.B.3–15, 2010.

[46] Liu, T., Z. Jiang, R. Liu, and S. Liu, A review of the multi-depot vehicle routing problem, in *Energy Procedia 13*, Singapore, 2011.

[47] Loxton, R., Q. Lin, and K. L. Teo, A stochastic fleet composition problem, *Computers & Operations Research*, 39(12):3177–3184, 2012.

[48] Macedo, R., C. Alves, J. Valério de Carvalho, F. Clautiaux, and S. Hanafi, Solving the vehicle routing problem with time windows and multiple routes exactly using a pseudo-polynomial model, *European Journal of Operational Research*, 214(3):536–545, 2011.

[49] Mingozzi, A., R. Roberti, and P. Toth, An Exact Algorithm for the Multi-Trip Vehicle Routing Problem, *INFORMS Journal on Computing*, 2012.

[50] Mole, R., Dynamic optimization of vehicle fleet size, *Operational Research Quarterly*, 26(1):25–34, 1975.

[51] New, C., Transport fleet planning for multi-period operations, *Operational Research Quarterly*, 26(1):155–166, 1975.

[52] Norin, A., T. A. Granberg, P. Värbrand, and D. Yuan, Integrating optimization and simulation to gain more efficient airport logistics, in *Eighth USA/Europe Air Traffic Management Research and Development Seminar*, USA, 2009.

[53] Oppen, J., A. Lokketangen, and J. Desrosiers, Solving a rich vehicle routing and inventory problem using column generation, *Computers & Operations Research*, 37(7):1308–1317, 2010.

[54] Parikh, S., On a fleet sizing and allocation problem, *Management Science*, 23(9):972–977, 1977.

[55] Redmer, A., J. Zak, P. Sawicki, and M. Maciejewski, Heuristic Approach to Fleet Composition Problem, *Procedia - Social and Behavioral Sciences*, 54:414–427, 2012.

[56] Rieck, J. and J. Zimmermann, A new mixed integer linear model for a rich vehicle routing problem with docking constraints, *Annals of Operations Research*, 181(1):337–358, 2010.

[57] Roling, P. C. and H. G. Visser, Optimal Airport Surface Traffic Planning Using Mixed-Integer Linear Programming, *International Journal of Aerospace Engineering*, 2008(1):1–11, 2008.

[58] Schlegel, A., *Bodenabfertigungsprozesse im Luftverkehr*, Gabler, Wiesbaden, 2010.

[59] Simms, B., B. Lamarre, A. Jardine, and A. Boudreau, Optimal buy, operate and sell policies for fleets of vehicles, *European Journal of Operational Research*, 15(2):183–195, 1984.

[60] Toth, P. and D. Vigo, *The vehicle routing problem*, SIAM, Philadelphia, 2002.

[61] Vanderbeck, F. and L. A. Wolsey, An exact algorithm for IP column generation, *Operations Research Letters*, 19(4):151–159, 1996.

[62] Wu, P., J. Hartman, and G. Wilson, An integrated model and solution approach for fleet sizing with heterogeneous assets, *Transportation Science*, 39(1):87–103, 2005.

[63] Wu, W. M., An approach for measuring the optimal fleet capacity: Evidence from the container shipping lines in Taiwan, *International Journal of Production Economics*, 122(1):118–126, 2009.

[64] Wyatt, J., Optimal Fleet Size, *Journal of the Operational Research Society*, 12(3):186–187, 1961.