# Optimizing the routing and scheduling of airside belly cargo transportation

An AirportCreators case study of KLM Cargo at Amsterdam Airport Schiphol

Iris Scheer

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by


Iris Scheer


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To close, throughout this journey, I have come to realize – even more than when I wrote it in my Bachelor's thesis – how true Isaac Asimovs words are: *"education isn't something you can finish"*. And that is something I am grateful for, as it makes me even more excited to see what the future holds!

Iris Scheer
Schiphol-Rijk, March 2025

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# List of Abbreviations

| | |
|---|---|
| 1-1 | One-to-One |
| 1-M-1 | One-to-Many-to-One |
| AAS | Amsterdam Airport Schiphol |
| ACTP | Airside Cargo Transportation Problem |
| CCT | Current KLM Cargo Terminal |
| CD | Conceptual Design |
| CG | Column Generation |
| CR | Customer Rejection |
| DARP | Dial-a-Ride Problem |
| DD | Dynamic and Deterministic |
| DS | Dynamic and Stochastic |
| EA | Evolutionary Algorithm |
| FD | Future Design |
| GA | Genetic Algorithm |
| KPI | Key Performance Indicator |
| LR | Lagrangian Relaxation |
| LS | Local Search |
| M-M | Many-to-Many |
| MILP | Mixed-Integer Linear Programming |
| MIP | Mixed-Integer Programming |
| MSP | Machine Scheduling Problem |
| NCT | New KLM Cargo Terminal |
| PD | Problem Definition |
| PDP | Pick-up and Delivery Problem |
| RH | Rinse Hofstra |
| RQ | Research Question |
| SD | Static and Deterministic |
| SI | Swarm Intelligence |
| SPP | Set Partitioning Problem |
| SS | Static and Stochastic |
| SSS | Successive Subproblem Solving |
| TS | Tabu Search |
| TSP | Travelling Salesman Problem |
| TT | Travel times |
| ULD | Unit Load Device |
| VNS | Variable Neighborhood Search |
| VRP | Vehicle Routing Problem |
| VRPDP | Vehicle Routing Problem with Deliveries and Pick-ups |

# Contents

# Introduction

Amsterdam Airport Schiphol (AAS) is planning a potential restructuring of its Center area, which requires KLM Cargo to relocate its cargo terminal to AAS Southeast. This realocation of KLM Cargo brings significant logistical and operational changes, both inside and outside the cargo terminal. One of which to the airside cargo transportation  the movement of cargo between the cargo terminal and aircraft using the airports service roads. The relocation is particularly critical for cargo transported via passenger aircraft, as the resulting expanded service road network increases travel distances and introduces new complexities, such as the Kaagbaantunnel.

Airside cargo transportation is a vital component of the air cargo supply chain, requiring efficient and timely cargo movement to ensure shipments reach their intended flights without delay. Any disruption in this process can lead to missed flight connections, forcing cargo to be rebooked on later flights, which in turn disrupts supply chains, incurs financial consequences, and affects service quality. Airside cargo transportation is an important part of the air cargo supply chain, requiring efficient and timely cargo transport ensuring that cargo is transported. Delays in airside transportation can result in cargo missing its flight, meaning the cargo needs to be rebooked onto another flight. This disrupts the air cargo supply chain resulting in financial consequences and impacting service quality. Additionally, efficient airside cargo transportation is crucial for minimizing travel time and optimizing resource utilization which by themself influence manpower and fuel consumption.

A key aspect of the airside cargo transportation problem is recognizing that KLM Cargo and AAS have distinct perspectives and objectives. KLM Cargo prioritizes an timely, efficient, cost-effective transportation operation to maintain its service reliability, while AAS focuses on optimizing airport-wide traffic flow and infrastructure utilization. These differing priorities make it an intriguing challenge to evaluate how various transportation strategies, both within and outside the cargo terminal, impact airside cargo transportation and what implications they hold for both stakeholders.

Conducting this thesis in collaboration with AirportCreators provides an independent perspective on the problem, enabling an objective evaluation of the findings and their broader implications for both stakeholders involved. It also provided the opportunity to explore a new and innovative methodology - aligned with AirportCreators' values - by formulating a Mixed-Integer Linear Programming (MILP) model for airside cargo transportation, an area that had not been previously addressed.

This thesis is structured into two main parts. Part I presents the scientific paper, describing the research conducted during the thesis, including the methodology, results, and conclusion. Part II covers the literature study conducted prior to the research, providing a literature review, identifying the literature gap of this thesis, and outlining the research plan for the thesis.

# I

## Scientific Paper

# Optimizing the routing and scheduling of airside belly cargo transportation for a cargo hub airport

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**Abstract**

Airside cargo transportation is a critical component of the air cargo supply chain, requiring timing and coordination to minimize operational costs and ensure high service quality for the airline transporting the cargo. The Airside Cargo Transportation Problem (ACTP) addresses the efficient routing and scheduling of cargo vehicles carrying ULDs across the airport's service roads between the cargo terminal and passenger aircraft stands while adhering to operational and safety requirements. Key aspects of the ACTP include vehicle capacity utilization, differentiation between cargo commodities, and the consideration of time-dependent travel times. This paper presents a Mixed-Integer Linear Programming (MILP) formulation of the ACTP as a Set Partitioning Problem. The sets cover all possible consolidations of various cargo transportation requests on paths generated using preprocessing algorithms. The ACTP is computationally feasible by applying a rolling horizon-based heuristic. The model is applied to a case study at Amsterdam Airport Schiphol (AAS) after a potential relocation of KLM Cargo's terminal. This relocation provides a unique opportunity to evaluate various strategies to optimize airside cargo transportation and study the implications for both KLM Cargo and AAS. Two strategies were evaluated to optimize network capacity: one focusing on spatial distribution and the other on time distribution by using traffic predictions. While the spatial distribution strategy degrades the overall performance, the traffic prediction strategy resulted in poor solution quality due to increased model complexity. Accordingly, it could not be proven that its results are comparable to those of other strategies. In addition, two strategies examined the impact of different cargo terminal operational concepts on cargo transportation. The pull strategy, which schedules cargo to arrive at the aircraft stand just in time for loading, improved overall airside cargo transportation performance. In contrast, the push strategy, which transports cargo immediately after processing at the cargo terminal, resulted in a decline in overall airside cargo transportation performance.

## 1 Introduction

Airside cargo transportation is a critical part of the air cargo supply chain, requiring timing and coordination to ensure the movement of cargo between cargo terminals and aircraft stands. Adherence to flight schedules is the main driver for cargo transported in the belly of passenger aircraft, as these flights are rarely delayed to accommodate late cargo. Failure to deliver cargo to the aircraft within the specified timeframe results in it being left behind, meaning the cargo has to be rebooked onto another flight. This impacts not only the airline's service quality and reputation but also results in financial losses from cargo rebooking and unused belly cargo space, highlighting the importance of reliable airside cargo transportation.

During airside cargo transportation of belly cargo, cargo is transported between cargo terminals and aircraft stands using the airport's service roads. In this paper, one cargo unit, whether an air pallet, baggage cart carrying mailbags, animal cage, etc., is referred to as a Unit Load Device (ULD). Airside transportation is divided into two flows: inbound and outbound. Inbound cargo arrives by aircraft at an aircraft stand, where the ULDs are unloaded onto dollies and parked at the aircraft stand. Then, vehicles pick up these ULDs and transport them to a cargo terminal. A directing center assigns specific ULDs to vehicles, enabling them to consolidate multiple ULDs from different aircraft stands into a ULD train, with a maximum capacity of six ULDs [HSE Risk and Compliance, ]. In the terminal, these ULDs are forwarded to landside transport or transits to the outbound cargo flow. The latter also arrives at the cargo terminal by landside transport. In the terminal, the outbound cargo ULDs are prepared for flight and loaded onto dollies, after which a control center consolidates them into a train of ULDs of up to six ULDs [HSE Risk and Compliance, ]. Subsequently, these ULD trains are parked at the cargo terminal's shunting area and assigned to vehicles that transport the ULDs from the terminal to the aircraft stand of their corresponding flight.

The airside cargo transportation problem focuses on the routing and scheduling of vehicles to transport cargo while efficiently using vehicle capacity and differentiating between commodity types. Efficient vehicle capacity

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utilization is determined by consolidating ULDs into inbound and outbound ULD trains and reducing empty vehicle movements by combining the transportation of inbound and outbound trains for one vehicle. Both influence the required number of vehicles and consequently impact the total travel time and travel distances of all vehicles. Cargo is classified into various commodity types, each with specific handling requirements. These requirements can be categorized based on transportation and time constraints. Transportation requirements focus on how the cargo moves across airside, including the type of ULD used and cargo consolidation into a ULD train. Time requirements refer to the specified pick-up and delivery time windows at the cargo terminal and aircraft stand. By addressing these distinct requirements, airside cargo transportation can accommodate the diverse needs of different commodity types.

The limited available service roads on airside make airside cargo transportation vulnerable to service road conditions such as congestion and road closure, as it impacts travel times. Service road travel times highly depend on road capacity and traffic flow and vary throughout the day. Failing to account for travel time variability can result in cargo missing its delivery deadline, leading to reduced service quality. If traffic flow approaches the road's maximum capacity, travel speed decreases resulting in increased travel times [Greenshields et al., 1935]. When flow exceeds the maximum capacity, congestion occurs, causing a further increase in travel time. The traffic flow resulting in travel time variability on airport service roads is influenced not only by cargo transport vehicles but mainly by the broader traffic flow, which is predominantly generated by ground-handling vehicles, authority vehicles, contractors, etc. Most of these vehicles' movements are constant throughout the day, whereas the traffic flow of ground-handling vehicles fluctuates, driven by the demand for aircraft turnaround based on flight schedules. As a result, travel times across the network are time-dependent, fluctuating with the road's traffic flow. Incorporating these time-dependent travel times better reflects real-world conditions, improving the model's reliability.

During the real-life application of the airside cargo transportation problem, operational inputs arrive and update continuously throughout the day of operation. These inputs comprise airside road travel times, aircraft stand allocation, aircraft arrival and departure times, and landside cargo deliveries at the cargo terminals. Considering this dynamic nature of the problem ensures that airside cargo transportation remains adaptive to changing conditions.

This paper presents a model for the Airside Cargo Transportation Problem (ACTP), which considers the routing and scheduling of cargo vehicles carrying ULDs across airport service roads with time-dependent travel times while efficiently using vehicle capacity and accounting for differentiation among commodity types. The model is applied to a case study at Amsterdam Airport Schiphol (AAS) to evaluate the impact of the potential relocation of the KLM Cargo terminal from Schiphol Centre to Schiphol Southeast on airside cargo transportation due to the restructuring of AAS Centre. The relocation would increase the airside network over which cargo is transported, as the distance between the new cargo terminal and the passenger aircraft stands would increase substantially. Additionally, a tunnel, which is prone to closure, is included in the network increasing its complexity. A key aspect of this case study is the differing objectives of its two main stakeholders, KLM Cargo and AAS, in airside cargo transportation. KLM Cargo prioritizes efficiency and cost-effectiveness, while AAS focuses on optimizing airport-wide network capacity utilization. The case study is conducted independently of both stakeholders in collaboration with AirportCreators [1], ensuring an objective evaluation of the findings and their broader implications for all stakeholders.

The relocation facilitates a unique opportunity to evaluate various strategies to optimize airside cargo transportation and study the implications for both stakeholders. Two strategy levels are defined: network-level strategies, which influence the use of the network's capacity, and terminal-level strategies, which affect the terminal operating procedures. The latter has implications for airside cargo transportation. Consequently, this paper aims to determine whether there are network-level and terminal-level strategies that can optimize the airside belly cargo transport between cargo terminals and passenger aircraft across the airport's service roads.

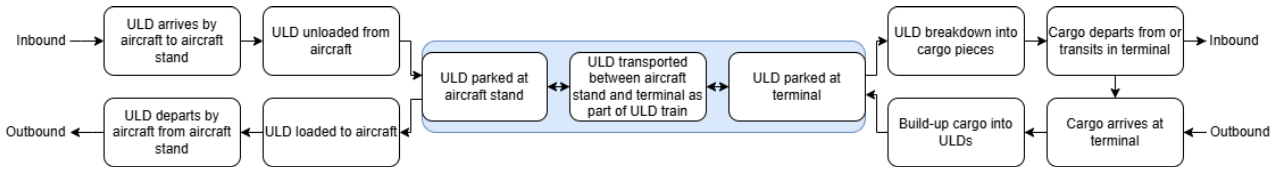

Figure 1: Scope of the Airside Cargo Transportation Problem (highlighted in the blue box).

The scope of this paper is limited to the airside transportation of belly cargo between the cargo terminal's shunting area, and the passenger aircraft stands as visualized in Figure 1. The remainder of this article is organized as follows. Section 2 reviews related literature and presents the research gap filled by this paper. Section 3 describes the ACTP formulation and solution approach. Then, the KLM Cargo case study is explained

[1] AirportCreators is a consultancy specializing in the field of airport development

in Section 4. Next, the strategies and corresponding results are presented and evaluated in Section 5. Finally, a conclusion is drawn and recommendations for future research are provided in Section 6.

# 2 Literature Review

Airside cargo transportation involves moving goods between paired pick-up and delivery locations, closely aligning with Pickup and Delivery Problems (PDPs). Accordingly, Subsection 2.1 explores relevant PDPs to provide insights into optimizing routing and scheduling. Next, Subsection 2.2 examines other closely related airport transportation problems to gain insight into the state of literature in these fields.

## 2.1 Pick-up and Delivery Problem

The PDP is a generalization of the Vehicle Routing Problem (VRP), which describes the problem of finding a set of least-cost routes for vehicles to visit every customer exactly once while starting and ending each route from a depot [Dantzig and Ramser, 1959]. While the VRP enforces deliveries from depots to customers, the PDP generalizes this by requiring both pick-up and delivery locations for each request, ensuring that all demands follow predefined origin-destination pairs. Lokin [Lokin, 1979] first described the PDP. Since then, the PDP has been a widely studied problem with numerous variations, which are extensively reviewed in the following surveys: Berbeglia et al. [Berbeglia et al., 2007], Cai et al. [Cai et al., 2023], Oyola et al. [Oyola et al., 2018], and Psaraftis et al. [Psaraftis et al., 2016].

This paper studies a variant of the PDP with transportation requests that cannot be rejected and have predefined origins and destinations. All PDPs discussed share these characteristics. In addition, this paper's PDP variant involves hard pick-up and delivery time windows, limited vehicle capacity, time-dependent travel times, road closure, explicit routing throughout the network, and commodity differentiation. Dumas et al. [Dumas et al., 1991], Narny and Barnes [Nanry and Barnes, 2000], and Chami et al. [Chami et al., 2018] have studied PDPs with a combination of this first two characteristics. All three PDPs determine the routing between customer nodes, assuming direct travel between nodes and excluding explicit sc of throughout the network. This means they do not ensure safe separation between vehicles and the problem formulation does not include intersection nodes of the network.

Time-dependent travel times are described in terms of the PDP by Haghani and Jung [Haghani and Jung, 2005] and by Schilde et al. [Schilde et al., 2014] in terms of the dial-a-ride problem, a generalization of the PDP transporting passengers. Both papers show that considering traffic condition variations as time-dependent travel times significantly outperform models that do not. Haghani and Jung [Haghani and Jung, 2005] specify a time-dependent value for each time period on every road within the considered network. In contrast, Schilde et al. [Schilde et al., 2014] apply stochastic travel times that become available once a vehicle starts traveling along its assigned paths. In addition, Haghani and Jung [Haghani and Jung, 2005] also demonstrate that the model works well in scenarios where accidents cause substantial congestion. This effect of an accident can be compared to the closure of the tunnel. Nevertheless, both papers allow pick-up and delivery time windows violation.

The PDP becomes computationally infeasible for large-scale instances as it is an NP-hard problem [Cordeau et al., 2008]. Subsequently, the PDP is solved using exact methods for small instances of up to 25 requests [Parragh et al., 2006]. Large-scale instances require alternative solution approaches, with various options available. The solution approaches of the previously mentioned papers are shortly mentioned as an indication of the various options. Dumas et al. [Dumas et al., 1991] formulate the PDP as a Set Partitioning Problem (SPP). An SPP partitions a set into smaller subsets and seeks to determine the minimum-cost solution in which each element is assigned to exactly one subset. In this context, the PDP requires selecting a subset of all feasible paths to ensure that every pick-up and delivery request is fulfilled exactly once. The resulting PDP is solved using column generation, providing an optimal solution for instances up to 55 requests. Narny and Barnes [Nanry and Barnes, 2000] use a reactive tabu search as a solution approach. Chami et al. [Chami et al., 2018] divide the PDP using a rolling horizon approach of isolated subproblems, which are solved sequentially. These subproblems of up to 25 requests are solved using a genetic algorithm. Haghani and Jung [Haghani and Jung, 2005] uses a genetic algorithm, while Schilde et al. [Schilde et al., 2014] uses a block scheduling algorithm.

## 2.2 Airport Airside Transport

To the best of the author's knowledge, the only publicly available research on airside cargo transportation examines the impact of various transportation strategies on on-time cargo delivery to aircraft under clean apron conditions [van Rugge, 2019]. The study uses a simulation to evaluate push, pull, and variations of such strategies. In addition to focusing on outbound cargo, that study does not account for travel time variations, commodity distinction, or dynamic changes in road availability. Other studies regarding airside transportation consider other ground-handling activities. Guo et al. [Guo et al., 2020] applies a PDP using a genetic algorithm to solve airside baggage transportation, and Zhu et al. [Zhu et al., 2022] studies a VRP solved by using a branch-and-bound algorithm for the combined operation of two ground-handling services. Both studies show similarities with the problem studied in this paper, as they consider paired demand, time windows, and no request rejections. The first study also considers limited vehicle capacity. However, time-dependent travel times, road closure, explicit routing throughout the network, and commodity differentiation remain undiscussed in these study contexts.

Atkin et al. [Atkin et al., 2010] surveys the frequently studied aircraft ground routing problem in which aircraft movement is scheduled between the runway and parking positions. Guépet et al. [Guépet et al., 2016] consider a ground routing problem with predetermined alternate paths, which allows the problem to be solved as an SPP using a Rolling Horizon algorithm. This paper explicitly schedules the aircraft throughout the network, including intersection nodes into the problem formulation. However, this paper allows time window violations and only considers a one-way trip between runway and aircraft stands instead of round trips. Moreover, this problem does not consider the transportation of goods.

### 2.3 Research gap

This paper presents a Mixed-Integer Linear Programming (MILP) formulation for the ACTP that is a combination of Guépet et al. [Guépet et al., 2016], Chami et al. [Al Chami et al., 2018], and Haghani and Jung [Haghani and Jung, 2005]. Chami et al. [Chami et al., 2018] provide the base for a multi-period PDP which can be solved using a rolling horizon approach. This is extended by the explicit routing throughout the network by including intersection nodes into the problem formulation as presented by Guépet et al. [Guépet et al., 2016]. Additionally, Guépet et al. [Guépet et al., 2016] also provide the base to solve the problem as an SPP. Haghani and Jung [Haghani and Jung, 2005] provide the base for incorporating time-dependent travel times and tunnel closure. Moreover, this combination of models is extended by the differentiation between cargo commodities.

Table 1: Comparison of MI(L)P models discussed in the literature review. HTW = Hard Time Window, VC = Vehicle Capacity, TTT = Time-dependent Travel Time, RC = Road Closure, ER = Explicit Routing, CD = Commodity Differentiation.

| Reference | HTW | VC | TTT | RC | ER | CD | Solution Approach |
|---|---|---|---|---|---|---|---|
| [Dumas et al., 1991] | ✓ | ✓ | | | | | SPP + column generation |
| [Nanry and Barnes, 2000] | ✓ | ✓ | | | | | Reactive tabu search |
| [Chami et al., 2018] | ✓ | ✓ | | | | | Rolling horizon + genetic algorithm |
| [Haghani and Jung, 2005] | | ✓ | ✓ | ✓ | | | Genetic algorithm |
| [Schilde et al., 2014] | | ✓ | ✓ | | | | Block scheduling algorithm |
| [Guo et al., 2020] | ✓ | ✓ | | | | | Genetic algorithm |
| [Zhu et al., 2022] | ✓ | | | | | | Branch-and-bound algorithm |
| [Guépet et al., 2016] | | | | | ✓ | | SPP + rolling horizon |

## 3 Methodology

The ACTP is formulated as an SPP. Implementing the problem requires executing a preprocessing algorithm to generate the required sets and variables and then solving the ACTP. First, the problem formulation and the corresponding notation are provided in Subsection 3.1. Then, the set generation algorithm is described in Subsection 3.2. The mathematical formulation of the ACTP and its solution approach is presented in Subsection 3.3 and Subsection 3.4, respectively.

### 3.1 Notation

Let $G = (V, A)$ be a directed transportation network (see Figure 2), where $V$ is the set of nodes and $A$ is the set of arcs. For the arcs, a distinction is made between main service road arcs ($A_m$), designed to distribute vehicles throughout the network, and access road arcs ($A_a$), which facilitate vehicle access to aircraft stands. For any arc $v \to w \in A$, let $T_{vw}$ be the minimum travel time and $D^{\tau}_{vw}$ delay factor from node $v$ to node $w$ during time period $\tau$. The delay factors for the arcs are time-dependent. Accordingly, the travel time is calculated as the minimum travel time multiplied by the arc's delay factor for the period $\tau$ and hence time-dependent. The nodes are categorized into three types ($V = V_i \cup V_s \cup \{O, D\}$): intersection nodes $V_i$, aircraft stand nodes $V_s$, and depot nodes $\{O, D\}$. The intersection nodes $V_i$ present intersections where directional choices are made. Two vehicles should have a minimum separation time at each intersection node of $S$ seconds. Aircraft stand nodes $V_s$ represent the location at the aircraft stand where vehicles can pick up or deliver cargo for a flight. The depot node represents the cargo terminal from which all paths start and terminate. They are modeled as a separate origin $O$ and destination $D$ node, respectively. Vehicles can wait at aircraft stand nodes and the depot

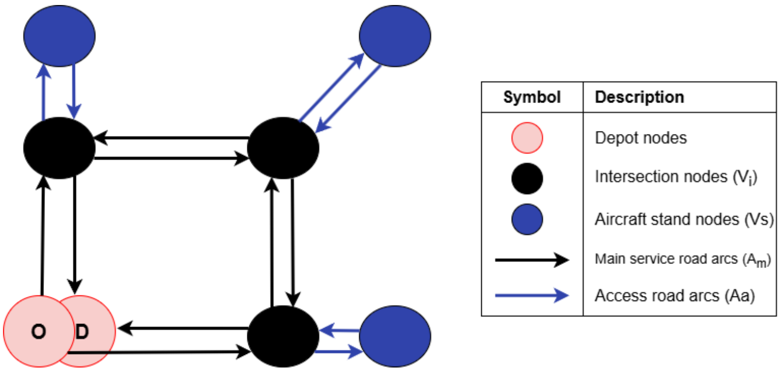

Figure 2: Visual representation of the graph $G$.

node $O$, whereas no waiting is allowed at the intersection nodes. It is assumed that the coupling or decoupling of ULDs to the train takes 120 seconds ($H$), including all handling required by the driver. This handling time is modeled as additional handling time on the arc between the aircraft stand node and its two corresponding access road arcs.

The fleet of homogeneous vehicles is represented by set $K$, each with a maximum capacity of a train of six ULDs. Cargo transportation requests are represented by set $R$. Each cargo transportation request involves transporting cargo either from the depot node to an aircraft stand node or in the reverse direction. A transportation request consists of one commodity type and, at most, six ULDs. Splitting a request is not allowed. Thus, each request $r$ has to be transported by one vehicle. If multiple commodities need to be picked up or delivered from one flight, they are treated as separate transportation requests. Each transportation request is associated with two distinct time windows. The time window $[\alpha_r^{\text{pick-up}}, \beta_r^{\text{pick-up}}]$ specifies the earliest and latest pick-up times of request $r$, while $[\alpha_r^{\text{delivery}}, \beta_r^{\text{delivery}}]$ denote the earliest and latest delivery times of request $r$. Evidently, a pick-up should precede the delivery of a request $r$. The specific values are defined by the transportation flow (inbound or outbound) and commodity type of the request.

A vehicle travels a round trip starting and ending at the depot on which it can visit one or multiple aircraft stands. A set of all paths $P$ are generated by Algorithm 3.2. Based on these paths, each intersection node $u$ is duplicated by the maximum number of times the node is visited across all paths and stored in set $V_u$. This duplication enables a vehicle $k$ to visit a node $u$ multiple times along a path $p$ if necessary.

A vehicle $k$ on a path $p$ can fulfill a request combination $c$ consisting of one or multiple requests from $R$. All possible request combinations are given by set $C$ generated by Algorithm 1. To fulfill a request combination $c$, a vehicle is assigned to a path $p$ from the request combination's set of alternate paths $P_c$, such that it visits the right aircraft stand nodes to pick up and/or deliver requests. For each request combination $c$ on a specific path $p$, the sequential nodes and arcs used in $p$ are denoted by $V^p$ and $A^p$. All alternate paths for a request combination $P_c$ are determined in Algorithm 1. Once a vehicle departs the depot, the path $p$ and the to-fulfill request combination $c$ on that path cannot be altered.

The ACTP differentiates commodity types by implying different transportation requirements and pick-up and delivery time windows. The problem distinguishes six commodities types: general, passive cooled, active cooled, express, secure, and live. General, passive cooled, and active cooled cargo comprises cargo with neither special transportation requests nor deviating time windows. While passive and active cooled cargo is transported in specialized ULDs that maintain the required temperature conditions, this distinction is not explicitly addressed in the ACTP, as all ULDs are assumed to be uniform. Express cargo is accepted at the cargo terminal shortly before a flight's departure. As a result, the pick-up and delivery time windows for outbound express cargo are closer to the departure time of the flight. Secure cargo, comprising high-value goods, requires security during airside transportation, while live cargo, consisting of living creatures, demands additional care. Accordingly, both commodity types have specific transportation requirements prohibiting their consolidation with any other commodity type during airside transport.

## 3.2 Set Generation Algorithm

Formulating the ACTP as an SPP, set $C$ should be generated before setting up the model. The Set Generation Algorithm (Algorithm 1) generates all feasible request combinations $C$ with corresponding paths to deliver one or multiple requests from $R$.

The algorithm starts by generating the set of paths $P$ that visits a permutation of aircraft stands, starting ($O$) and ending at the depot ($D$). First, the permutations of subsets of aircraft stand nodes ($SP$) are generated based on the maximum number of aircraft stands visited on one path ($S_{max}$). That means creating permutations of aircraft stand nodes ($V_s$) taking a subset of one aircraft stand, a subset of two aircraft stands, and so on, up to a subset of $S_{max}$ aircraft stands. Then, for each aircraft stand permutation in $SP$, all possible paths that

Table 2: Notation of the sets.

| Notation | Description |
|---|---|
| $V$ | Set of nodes indexed by $u$, $v$ or $w$ |
| $V_i$ | Subset of intersection nodes |
| $V_s$ | Subset of aircraft stand nodes |
| $V_s^p$ | Subset of aircraft stand nodes on path $p$ |
| $V^p$ | Subset of nodes in path $p$ |
| $V_u$ | Subset of duplicate nodes for intersection node $u$ |
| $A$ | Subset of arcs |
| $A^p$ | Subset of arcs in path $p$ |
| $A_m^p$ | Subset of main service road arcs in path $p$ |
| $A_a^p$ | Subset of access road arcs in path $p$ |
| $K$ | Set of vehicles indexed by $k$ |
| $R$ | Set of cargo transportation requests indexed by $r$ |
| $C$ | Set of transportation request combinations indexed by $c$ |
| $C_r$ | Subset of transportation request combinations containing request $r$ |
| $P$ | Set of paths indexed by $p$ |
| $P_c$ | Subset of alternate paths for transportation request combination $c$ |
| $P_u$ | Subset of paths containing node $u$ |

Table 3: Notation of the parameters.

| Notation | Description |
|---|---|
| $C_{max}$ | Maximum number of request $r$ to be fulfilled along a path $p$ |
| $D_{vw}^{\tau}$ | Delay factor of arc $(v, w)$ during time period $\tau$ |
| $H$ | Handling time in seconds to (de)couple ULDs at the aircraft stand |
| $S$ | Minimum separation time between vehicles at intersection nodes |
| $S_{max}$ | Maximum number of aircraft stands visited along a path $p$ |
| $TT_{vw}$ | Minimum travel time of arc $(v, w)$ |
| $[\alpha^{\tau}, \beta^{\tau}]$ | Earliest and latest time of time period $\tau$ |
| $[\alpha_O^p, \beta_O^p]$ | Earliest and latest departure time from depot node $O$ on path $p$ |
| $[\alpha_r^{\text{pick-up}}, \beta_r^{\text{pick-up}}]$ | Earliest and latest pick-up time of request $r$ |
| $[\alpha_r^{\text{delivery}}, \beta_r^{\text{delivery}}]$ | Earliest and latest delivery time of request $r$ |

visit all aircraft stands in the aircraft stand permutation are determined. Paths $P$, store the index of each path $p$ along with the set of sequential nodes $V^p$, sequential arcs $A^p$, and the aircraft stand nodes visited on the path $V_s^p$. To constrain the size of the path set $P$, it is assumed that only the shortest path is used between aircraft stands. However, between an aircraft stand and the depot, in either direction, all possible paths are considered.

Then, the set of request combinations $RC$ is determined containing all possible combinations of a subset containing one request, two requests, and so on, up to the maximum number of requests per combination ($C_{max}$) are generated. It is important to note that the size of set $RC$ grows factorially as the size of the set $R$ increases, as this impacts the model size significantly.

Then, for each request combination $c$ in $RC$, it is determined which aircraft stands $s$ need to be visited to fulfill all requests in $rc$. Accordingly, all paths that visit these aircraft stands $s$ are retrieved from the set $P$ and stored in set $P_c$. For all these alternate paths for request combination $c$ in $P_c$, the load and departure time from the depot node $O$ are calculated. During the load calculation, the number of ULDs carried during each step along the path $p$ is determined ($L$). The depot departure time window calculation determines the earliest and latest time to leave the depot node $O$ to fulfill all requests in the request combination $c$ within their pick-up and delivery time windows on path $p$ ([ $\alpha_O^p$,$\beta_O^p$]). A path from $P_c$ can be infeasible for request combination $c$ in two ways. Firstly, the path $p$ is infeasible if, at any step, the maximum vehicle capacity of six ULDs is exceeded or if a secure or live commodity is transported alongside any other commodity. Secondly, the path $p$ is infeasible for that request combination $c$ whenever not all requests can be delivered within their defined pick-up and delivery time windows. If the request combination $c$ on a path $p$ is feasible based on the load and the depot departure time window, it is stored in the $C$ along with the sequential set of nodes $V^p$ and arcs $A^p$ of path $p$ and depot departure time window [ $\alpha_O^p$,$\beta_O^p$].

## 3.3 Airside Cargo Transportation Problem

This ACTP model aims to efficiently route and schedule vehicles to fulfill all transportation requests in $R$ by selecting the optimal subset of request combinations of $C$ on their shortest paths in terms of travel time. The problem considers vehicle capacity utilization while accounting for commodity differentiation and time-dependent travel times. The objective is to minimize the total travel time of all vehicles, as this metric indirectly addresses multiple aspects of the problem, including maximizing the number of requests transported per vehicle, reducing travel distance, and minimizing the number of vehicles used. The decision variables of this problem

**Algorithm 1** Set Generation Algorithm

**Require:** $S_{max}$, $G$, $R$, $C_{max}$

$SP \leftarrow$ All aircraft stand permutations $SP$ based on $S_{max}$
$P \leftarrow$ All possible paths using $G$ for each aircraft stand permutations $SP$

$RC \leftarrow$ Generate Request Combinations $C$ based on requests $R$ using $C_{max}$
$C \leftarrow \{\}$

**for** each $c$ in $RC$ **do**
  Determine the aircraft stands $s$ to visit to fulfill all requests in $c$
  $P_c \leftarrow$ All paths that visit aircraft stands $s$ to fulfill $c$

  **for** each $p$ in $P_c$ **do**
    Determine load $L$ of $c$ on each step of path $p$
    Determine depot departure time window $[\alpha_O^p, \beta_O^p]$ for $c$ on path $p$ using the minimum travel times in $G$

    **if** $L$ or $[\alpha_O^p, \beta_O^p]$ not feasbile **then**
      $C \leftarrow C \setminus \{c\}$
    **else**
      $C[c,p] \leftarrow$ {nodes: $V^p$, arcs: $A^p$, departure time window: $[\alpha_O^p, \beta_O^p]$}
**return** C

are defined in table 4.

Table 4: Notation of the decision variables.

| Notation | Description |
|---|---|
| $x_k^p$ | = 1 if vehicle $k$ uses path $p$, = 0 otherwise |
| $y_k^{cp}$ | = 1 if vehicle $k$ uses path $p$ to deliver the pick-up and delivery request combination $c$, = 0 otherwise |
| $z_{klvw}$ | = 1 if the visit of vehicle $k$ arrives at node $v$ before node vehicle $l$ at node $w$, with $v$ and $w$ being duplicate of node $u$, = 0 otherwise |
| $b_{kvw}^\tau$ | = 1 if vehicle $k$ starts to travel from node $v$ to node $w$ in time period $\tau$, = 0 otherwise |
| $t_{kv}^p$ | = time vehicle $k$ reaches node $v$ through path $p$ |

The mathematical Mixed-Integer Programming (MIP) model of the ACTP is formulated as follows:

$$\min \quad \sum_{k\in K}\sum_{p\in P}(t_{kD}^p - t_{kO}^p) \tag{1}$$

subject to:

$$\sum_{k\in K}\sum_{c\in C_r}\sum_{p\in P_c} y_k^{cp} = 1 \qquad \forall r\in R \tag{2}$$

$$\sum_{p\in P} x_k^p \leq 1 \qquad \forall k\in K \tag{3}$$

$$y_k^{cp} \leq x_k^p \qquad \forall k\in K, c\in C, p\in P_c \tag{4}$$

$$\sum_{c\in C}\sum_{p\in P_c} y_k^{cp} = \sum_{p\in P} x_k^p \qquad \forall k\in K \tag{5}$$

$$t_{kv}^p \leq M * x_k^p \qquad \forall k\in K, p\in P, v\in V^p \tag{6}$$

$$t_{kO}^p \geq \alpha_O^p * x_k^p - M*(1-y_k^{cp}) \qquad \forall k\in K, c\in C, p\in P_c \tag{7}$$

$$t_{kO}^p \leq \beta_O^p * x_k^p + M*(1-y_k^{cp}) \qquad \forall k\in K, c\in C, p\in P_c \tag{8}$$

$$t_{kw}^p - t_{kv}^p = TT_{vw} * \sum_{\tau\in T}(D_{vw}^\tau * b_{kvw}^\tau) * x_k^p \qquad \forall k\in K, p\in P, (v,w)\in A_m^p \tag{9}$$

$$t_{kw}^p - t_{kv}^p \geq H/2 + TT_{vw} * \sum_{\tau\in T}(D_{vw}^\tau * b_{kvw}^\tau) * x_k^p \qquad \forall k\in K, p\in P, (v,w)\in A_a^p \tag{10}$$

$$\sum_{\tau\in T} b_{kvw}^\tau = x_k^p \qquad \forall k\in K, p\in P, (v,w)\in A^p \tag{11}$$

$$t_{kv}^p \geq \alpha^\tau * b_{kvw}^\tau \qquad \forall k\in K, p\in P, (v,w)\in A^p, \tau\in T \tag{12}$$

$$t^p_{kv} < \beta^\tau + M*(1-b^\tau_{kvw}) \qquad \forall k \in K, p \in P, (v,w) \in A^p, \tau \in T \quad (13)$$

$$z_{klvw} \leq \sum_{p \in P_u} x^p_k \qquad \forall k,l \in K, k \neq l, u \in V, v,w \in V_u \quad (14)$$

$$z_{lkwv} \leq \sum_{p \in P_u} x^p_l \qquad \forall k,l \in K, k \neq l, u \in V, v,w \in V_u \quad (15)$$

$$z_{klvw} + z_{klvw} \leq 1 \qquad \forall k,l \in K, k \neq l, u \in V, v,w \in V_u \quad (16)$$

$$\sum_{p \in P_w} t^p_{lw} \geq S + \sum_{p \in P_v} t^p_{kv} - M*(1-z_{klvw}) \qquad \forall k,l \in K, k \neq l, u \in V, v,w \in V_u \quad (17)$$

$$z_{klvw} + z_{lkwv} \geq -1 + \sum_{p \in P_u} x^p_k + \sum_{p \in P_u} x^p_l \qquad \forall k,l \in K, k \neq l, u \in V, v,w \in V_u \quad (18)$$

$$x^p_k \in \{0,1\} \qquad \forall k \in K, p \in P \quad (19)$$

$$y^{cp}_k \in \{0,1\} \qquad \forall k \in K, c \in C, p \in P_c \quad (20)$$

$$z_{klvw} \in \{0,1\} \qquad \forall k,l \in K, k \neq l, u \in V, v,w \in V_u \quad (21)$$

$$b^\tau_{kvw} \in \{0,1\} \qquad \forall k \in K, (v,w) \in A, \tau \in T \quad (22)$$

$$t^p_{kv} \geq 0 \qquad \forall k \in K, v \in V, p \in P \quad (23)$$

The objective function (1) minimizes the total travel time of all vehicles, defined as the arrival time at the depot node ($O$) minus the departure time at the depot node ($O$) for all vehicles.

All constraints are divided into four types: request combination and path selection constraints, time constraints, precedence constraints, and variable type constraints. The first four constraints consider the request combination and path selection constraints. Constraint 2 ensures that every request $r$ is fulfilled in one request combination $c$ on one path $p$. Constraint 3 ensures that every vehicle $k$ drives at most one path $p$. Constraint 4 addresses that a vehicle can only fulfill a request combination $c$ on a certain path $p$ if it also travels along that path $p$. Constraint 5 ensures consistency between selecting a path $p$ and assigning a request combination $c$ for each vehicle $k$.

The following seven constraints are time constraints. Constraint 6 regulates that arrival time at a node $v$ of vehicle $k$ on path $p$ can only be higher than zero if vehicle $k$ travels along path $p$. Constraint 7 and 8 enforces that if a vehicle $k$ uses path $p$ to deliver request combination $c$, then vehicle $k$ should leave the depot $O$ within the departure time window $[\alpha^p_O,\ \beta^p_O]$. Constraints 9 and 10 include the time-dependent travel times into the formulation and make it non-linear. Constraint 9 addresses that the travel time of $k$ across arc $(v,w)$ is exactly equal to the minimum travel time of that arc multiplied by the delay factor of the time period $\tau$ in which $k$ start to travel along this arc. Constraint 10 implies the same but allows waiting of vehicle $k$ at the aircraft stand nodes. Constraint 11 - 13 ensure that the decision variable $b^\tau_{kvw}$ is equal to one if vehicle $k$ start to travel across arc $(v,w)$ during time period $\tau$.

The next five constraints address the precedence relations between vehicles at an intersection node. Constraints 14 and 15 enforce that the precedence relation between vehicle $k$ and $l$ is only defined when vehicle $k$ and $l$ visit one of the duplicate nodes of $u$ on their path $p$. Constraint 16 ensures that for every visit to a duplicate node of $u$ on the paths of two vehicles, there exists a precedence relationship. Next, constraint 17 ensures that if vehicle $k$ and $l$ visit a duplicate of node $u$ on their paths, their arrival times are separated by the minimum separation time $S$. Constraint 18 enforces that if vehicle $k$ and $l$ visit a duplicate of node $u$ on their paths, either one of the vehicles visits the node first.

Finally, constraints 19 up until 23 define the domains of the decision variables.

## 3.4 Solution approach

The ACTP, as described in Subsection 3.3, is a generalization of the NP-hard VRP and becomes computationally infeasible for large-scale instances. The computational burden is reduced by solving the ACTP using a Rolling Horizon-based heuristic, which divides the problem into smaller subproblems with shorter time horizons. Each subproblem includes only a subset of transportation reuqest that can be fulfilled within its respective time horizon. This approach ensures that large-scale instatnce are broken down into computationally feasible subproblems.

First, the general description of the rolling horizon algorithm for the ACTP is described in Subsubsection 3.4.1. Accordingly, specific details of this formulation are explained in depth in the following subsections: Subsubsection 3.4.2 describes the greedy initial solution heuristic, Subsubsection 3.4.3 describes the mathematical subproblem formulation, and Subsubsection 3.4.4 details the precedence constraints used to resolve separation violations.

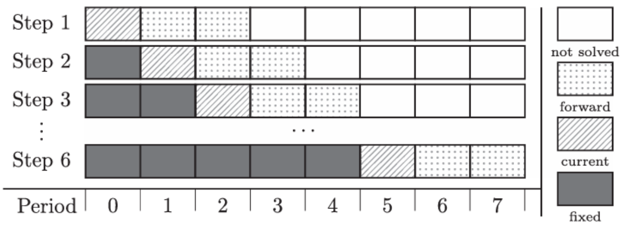

Figure 3: Schematic representation of rolling horizon algorithm with a total planning horizon of seven periods ($\tau_s = 7$ ) and two forward horizons ($f = 2$) [Glomb et al., 2022].

#### 3.4.1 Rolling Horizon formulation

The problem is divided into smaller, sequential subproblems with a fixed horizon length solved iteratively to solve the ACTP problem for the total planning horizon $H$. Each subproblem has two horizons: a current horizon ($H_\tau$) and a forward horizon ($H_f$). The current horizon $H_\tau$ represents a time period of length $\Delta t$. The forward horizon $H_f$ immediately follows $H_\tau$ and spans a time period of $\Delta t$ multiplied by the number of forward horizons $f$ included in the subproblem. In every step of the rolling horizon algorithm, the subproblem is built and solved considering $H_\tau$ and $H_f$. Once solved, the decision variables within $H_\tau$ are fixed to guide and constrain subsequent subproblems during the next step. This process is repeated iteratively, advancing $H_\tau$ and $H_f$ by $\Delta t$ for each subproblem until the total planning horizon $H$ is covered. Figure 3 provides a schematic representation of the rolling horizon algorithm. The overlapping horizons between subproblems ensure solution quality as the approach assures continuity and avoids short-term decisions that could arise from solving each horizon in isolation. Nevertheless, it should be outlined that the combined solution of all subproblems does not guarantee an optimal solution for the entire problem's horizon [Glomb et al., 2022].

The rolling horizon algorithm for the ACTP is provided in Algorithm 2 and works as follows: First, the required parameters and sets are obtained and generated: graph $G$ (including the nodes $V$ and arcs $A$), total planning horizon $H$, time period length $\Delta t$, number of forward horizons $f$, all paths $P$ based on graph $G$ (calculated by line 1-2 of Algorithm 1), initial time period $\tau = 0$, and the final time period $\tau_s$. After that, the iterative loop to solve each subproblem is initiated. This loop is finished after the time period $\tau$ equals the final time period $\tau_s$.

Within each iteration, four steps are executed: defining parameters and sets for the subproblem, building and initially solving the subproblem, resolving minimum separation violations, and fixing variables. First, the relevant parameters and sets are defined. The current horizon $H_\tau$ and forward horizon $H_f$ are updated in accordance with the current time period $\tau$. The delay factors parameters for all arcs are updated for time period $\tau$. Then, all requests $R$ to be fulfilled during the subproblem's horizon ($H_\tau \cup H_f$) are identified. Subsequently, Algorithm 1 determines all possible request combinations $C$ based on the set of requests $R$ of the subproblem. This algorithm is applied from lines 4 to 19 as presented in Subsection 3.2, except for the depot departure time window calculation in line 13. Instead, the depot departure time window is determined based on the actual travel times for each arc, calculated by multiplying the arcs minimum travel time $TT$ by the applicable delay factor during the subproblem's time period $\tau$. For each request combination in $C$, only the shortest path in terms of actual travel time is retained reducing the size of set $C$ substantially. Next, the set $K$ is constructed, consisting of two subsets. $K_n$ represents vehicles with unassigned request combinations and $K_e$ represents vehicles that have been assigned to a request combination and departed from the depot $O$ during the previous, current horizon $H_{\tau-1}$ but did not return to the depot $D$ in that horizon. These vehicles are included because their scheduling steps are not yet fully fixed, making them integral to the current subproblem's formulation. The size of the unassigned vehicle set $K_n$ is determined using an initial feasible solution generated by a greedy heuristic, detailed in Subsubsection 3.4.2. This heuristic provides an initial feasible solution that improves the computational efficiency of the subproblem in two ways, one of which is elaborated upon in the Subsubsection 3.4.2. At this stage, the heuristic's solution is used to estimate the size of the unassigned vehicle set $K_n$. The size of this set significantly impacts the size and computational efficiency of the subproblem.

In the second step, the ACTP subproblem is built using the defined sets and parameters. The formulation of the ACTP subproblem differs from the ACTP formulation presented in Subsection 3.3. The subproblem ACTP formulation is detailed in Subsubsection 3.4.3. The main difference is that the subproblem formulation excludes the precedence constraints as explained in Subsubsection 3.4.4). The problem's binary decision variables are warm started using the initial feasible solution determined by the greedy heuristic. Providing a good initial solution to the solver can improve the required computational time. Next, the subproblem ACTP is solved using a branch-and-bound algorithm, and an initial solution for the subproblem is obtained.

In the third stage, the initial subproblem's solution is checked for minimum separation violations, defined as two vehicles that arrive at a node with a separation of less than $S$ seconds. If at least one separation violation is detected, the subproblem formulation is extended by precedence constraints as further detailed in Subsubsection

3.4.4. Re-solving the subproblem including these constraints results in a solution without separation violations satisfying the problem's safety requirements.

In the final stage, the subproblem's solution is stored for vehicles that left within the current horizon $H_\tau$ are stored. This entails that for all vehicles that have left the depot node $O$ before $\beta^\tau$, the binary decision variables $x_k^p$ and $y_k^{cp}$ are fixed. Besides, all scheduling decision variables $t_{ku}^p$ smaller than $\beta^\tau$ are also fixed. A distinction is made between vehicles that finish their path before $\beta^\tau$, which are added to the finished vehicles set $K_f$, and those still en route at $\beta^\tau$; these are added to the en route vehicles set $K_e$. For the en route vehicles, its $(k, c, p)$ indices are stored in set $F$. The decision variables of the finished vehicles are stored to ensure all solutions can be combined after solving all subproblems. As a result, these vehicles are excluded from the next subproblem's formulation, while en route vehicles are included in the next subproblem formulation since their path $p$ still requires partial scheduling. Accordingly, their routing decision variables ($x_k^p$ and $y_k^{cp}$) are fixed, and their scheduling decision variables are partially fixed in the next subproblem's formulation.

Finally, the time period $\tau$ is increased by one. If the stopping condition is met, the stored objective functions and decision variables are combined into one solution of the entire planning horizon $H$.

**Algorithm 2** Rolling Horizon algorithm for the ATCP

**Require:** $G$, $H$, $\Delta t$, $f$
**Initialize**
Determine all paths $P$ based on $G$ using line 1-2 of Algorithm 1
$\tau = 0$
$\tau_s = H/\Delta t$

**while** $\tau \neq \tau_s$ **do**
    $H_\tau = [\tau * \Delta t,\ (\tau + 1) * \Delta t]$
    $H_f = [(\tau + 1) * \Delta t,\ (\tau + f + 1) * \Delta t]$
    Update delay factors $D_{vw}$ for time period $\tau$

    Determine $R$ within planning horizons $H_\tau$ and $H_f$
    Determine $C$ using line 4-19 of Algorithm 1
    Determine feasible initial solution using a greedy heuristic (Subsubsection 3.4.2)
    Create set of vehicles $K$ including en route vehicles $K_e$ based on greedy heuristic solution

    Build subproblem of ACTP for planning horizons $H_\tau$ and $H_f$ (Subsubsection 3.4.3)
    **if** $\tau > 0$ **then**
        Fix $x_k^p$, $y_k^{cp}$, $t_{kv}^p$ for en route vehicles $K_e$ using $F$

    Warmstart $x_k^p$ and $y_k^{cp}$ with greedy heuristic solution
    Solve subproblem ACTP for planning horizon $H_\tau$ and $H_f$

    Determine separation violations in solution
    **if** seperation violation **then**:
        Fix $x_k^p$ and $y_k^{cp}$ for remaining of subproblem
        Add precedence constraints 32-33
        Solve ACTP including precedence constraints for planning horizon $H_\tau$ and $H_f$

    Determine finished vehicles $K_f$ and en route vehicles $K_e$
    Store indexes $(k, c, p, v)$ of non-zero decision variables of en route vehicles $K_e$ to set $F$
    Store subproblem solution for finished vehicles $K_f$
    $\tau \leftarrow \tau + 1$

Combine solutions of all subproblems

### 3.4.2 Greedy heuristic

As previously stated, a heuristic has been included to warm-start the problem with an initial feasible solution to improve its computational time by making an informed estimate of the size of unassigned vehicles set $K_n$. Additionally, the feasible solution provides a good initial solution to the solver and can significantly improve its computational performance by guiding the solver toward promising regions of the solution space.

As the objective of the ACTP is to minimize the total travel time of all vehicles, it is apparent that solutions with a few vehicles are relatively good. Therefore, this heuristic aims to find a solution in which many requests are combined and transported by the same vehicle. Every combination $c$ in $C$ gets a score based on two targets. The first target is maximizing the number of requests in a combination, while the second is minimizing the total travel time of the path $p$ to deliver all requests in request combination $c$. By multiplying the first objective by $\overline{C}$, the first objective is prioritized above the second objective by multiplying the first. In this paper, $\overline{C}$ was set to 1000. This score is mathematically formulated as follows:

$$\text{score}(c, p) = \text{len}(c) * \overline{C} - \text{travel time path } p \tag{24}$$

The scores for all request combinations in $C$ are sorted in descending order. Iteratively, the highest-scoring request combination $c$ is added to the initial solution. To prevent duplication of requests in the initial solution, any request combination that includes a request already covered by the initial solution is removed from consideration. This process continues until the initial solution covers all requests in $R$ exactly once. At this point, the heuristic terminates, resulting in an initial feasible solution.

#### 3.4.3 Subproblem formulation

The subproblem formulation of the ACTP differs from the formulation presented in Subsection 3.3. Decision variables $x_k^p$, $y_k^{cp}$, and $t_{kv}^p$ are defined as previously. The precedence decision variable $z_{klvw}$ is not initially added to the subproblem formulation. Besides, as a subproblem lasts for one time period only, the travel time period decision variable $b_{kvw}^\tau$ is unnecessary. The subproblem formulation is presented below.

$$\min \quad \sum_{k \in K} \sum_{p \in P} t_{kD}^p - t_{kO}^p \tag{25}$$

Subject to:

$$(2-8), 19, 20, 23 \tag{26}$$

$$t_{kw}^p - t_{kv}^p = TT_{vw} * D_{vw} * x_k^p \qquad \forall k \in K_n, p \in P, (v, w) \in A_m^p \tag{27}$$

$$t_{kw}^p - t_{kv}^p \geq H/2 + TT_{vw} * D_{vw} * x_k^p \qquad \forall k \in K_n, p \in P, (v, w) \in A_a^p \tag{28}$$

$$t_{kw}^p - t_{kv}^p \geq TT_{vw} * D_{vw} * x_k^p + T * \delta_t \qquad \forall (k, c, p) \in F, (v, w) \in A^p \tag{29}$$

$$t_{kv}^p \geq \alpha^\tau - M * (1 - x_k^p) \qquad \forall k \in K_n, v \in V, p \in P \tag{30}$$

$$\sum_{p \in P} x_l^p \leq \sum_{p \in P} x_k^p \qquad \forall k, l \in K, \text{for } l < k \tag{31}$$

The subproblem formulation consists of the same objective function as described in Subsection 3.3 and consists of 16 constraints. The request combination and path selection constraints 2 - 5, the first three time constraints 6 - 8, and decision variable domain constraints 19, 20, and 23 from section 3.3 are still valid in this formulation. Constraint 27 addresses that the travel time of vehicle $k$ across arc $(v, w)$ is exactly equal to the minimum travel time of that arc multiplied by the arc's delay factor of the subproblem's time period $\tau$. Constraint 28 implies the same but allows vehicle $k$ to wait at aircraft stand nodes. Constraint 29 also implies the same but introduces an additional travel time if vehicle $k$ has been waiting before a closed tunnel in the previous horizon. $\delta_t$ is the waiting time for the closed tunnel, and $T$ is a binary parameter equal to one if the tunnel was closed during the previously current horizon $H_{\tau-1}$. Constraint 30 ensures that if vehicle $k$ travels along path $p$ it can only be scheduled during the current planning horizon or later. Constraint 31 introduces a distinction between vehicles in the homogeneous fleet, reducing symmetry in the problem and decreasing computational time.

#### 3.4.4 Precedence constraints

If a violation of the minimum separation is detected in the solution of a subproblem, they are resolved by introducing precedence constraints. To achieve this, first, the solution containing the separation violation is used to fix vehicles to their assigned paths ($x_k^p$) and request combinations ($y_k^{cp}$). The scheduling decision variable ($t_{kv}^p$) remains unfixed. Then, precedence constraints are added for all these vehicles of which the binary decision variables have been fixed. The precedence constraints consist of two types are formulated below.

$$z_{klvw} + z_{lkwv} = 1 \qquad \forall k, l \in K_c, k \neq l, u \in V^{p_k} \cap V^{p_l}, v, w \in V_u \tag{32}$$

$$t_{lw}^{p_l} \geq S + t_{kv}^{p_k} - M * (1 - z_{klvw}) \qquad \forall k, l \in K_c, k \neq l, u \in V^{p_k} \cap V^{p_l} v, w \in V_u \tag{33}$$

Constraint 32 guarantees that if vehicles $k$ and $l$ both visit a duplicate of node $u$ on their respective paths, the precedence of their visits is determined, ensuring that one vehicle visits the node before the other. Constraint 33 ensures that the arrival times of vehicle $k$ and $l$ at a duplicate node $u$ are separated by the minimum separation time $S$.

By incorporating these constraints at this stage into the subproblem formulation, they are included for vehicles that have been assigned to a path and only for a single path per vehicle. This approach significantly reduces the required number of precedence constraints to resolve separation violations, improving computational efficiency while preserving the precedence relations. As a result, the model's flexibility is reduced due to the fixed decision variables, which may lead to suboptimal solutions.

# 4 Case study

The model is applied to a case study at AAS to evaluate the impact of the potential relocation of KLM Cargo's terminal on airside cargo transportation. The relocation is driven by the potential restructuring of the AAS Centre, where the cargo terminal is currently located. Subsequently, the potential new location for the KLM Cargo terminal is at Schiphol Southeast. In Figure 4, the current cargo terminal is located to the right of roundabout 1 (RA1), and the potential new cargo terminal is beneath the Kaagbaan runway. This chapter first describes the stakeholder perspectives in Subsection , after which the case study input data is outlined in the subsequent sections. The AAS airside service road network is formulated as a mathematical graph $G$ as detailed in Subsection 4.2. In Subsection 4.3, the generation of the cargo transportation request data resulting in the set $R$ is explained. Subsection 4.4 explains how the delay factors for the AAS airside network are determined. Then, the concept and differences among input instances are detailed in Subsection 4.5.

## 4.1 Stakeholder perspectives

The two main stakeholders involved in the airside cargo transportation problem are KLM Cargo and AAS. KLM Cargo, responsible for airside cargo transportation, aims to ensure timely pick-up and delivery between the cargo terminal and aircraft stands while minimizing costs. These costs can be defined in multiple ways. Fuel consumption and sustainability are impacted by travel time and distance, while the required manpower is influenced by travel time and number of vehicles needed. Given the labor shortages and high labor costs, reducing manpower is important. In addition, the Kaagbaantunnel is a key operational concern, as the tunnel is prone to closure. When closed, vehicles must take the longer Kaagbaantunnel detour road, increasing travel time and costs. KLM Cargo wants to better understand the impact of the Kaagbaantunnel on its daily operations as well as minimize its reliance on this tunnel.

For AAS, maintaining adequate traffic flows on the service roads is essential to ensure efficient vehicle movements for all users. Increased traffic leads to congestion, causing delays that impact all road users. Delays in ground handling can result in late aircraft departures, affecting service quality and reducing the AAS' operational capacity. AAS is interested in optimizing the distribution of traffic across both time and space. Currently, traffic flow (especially on roads near the piers: Rinse Hofstra (RH) road South, DE-road, EF-road in Figure 4) is heavily influenced by flight schedules, as ground handling vehicles activity peak around aircraft turnaround times. At AAS, arrivals and departures are concentrated into seven peak periods throughout the day, leading to corresponding peaks in ground handling traffic. Additionally, there is a significant imbalance in road usage, with some routes being overutilized while others remain underused. Improving the time and spatial distribution of vehicles would help AAS maximize network capacity while maintaining reliable travel times for all users.

## 4.2 AAS airside road network

Figure 4 visually displays the graph of the airside road network at AAS for KLM Cargo's belly cargo transportation. The graph of AAS comprises 61 nodes and 126 arcs, among which 26 aircraft stands, 33 intersection nodes, and the cargo terminal nodes ($O$ and $D$). The aircraft stand nodes that are included in the network are the wide-body passenger aircraft stands generally used by KLM on the D, E, and F-pier, as most of KLM Cargo's belly cargo is transported by KLMs wide-body aircraft.

The weight of the arcs represents the minimum travel time between the two nodes. To do so, the distance of the arc is divided by the maximum travel speed along that arc. According to AAS regulations [HSE Risk and Compliance, ], the maximum speed limit is 30 km/h on service roads and 15 km/h on service roads with ramps. However, according to KLM Cargo, driving at a 30 km/h speed with a vehicle carrying a train of ULDs introduces a swing that leads to an increased risk of vehicle failure, ULD connection failure, and/or dropping objects from ULDs. This results in degrading airside cargo transportation performance and hence is unfavorable. Subsequently, the maximum speed for cargo vehicles is slightly corrected to 25 km/h. The maximum speed limit of 15 km/h remains on main service roads with ramps. Main service roads with ramps are indicated by parallel black lines in Figure 4. The Kaagbaantunnel detour arc is assumed to be in place, as this is a requirement for KLM Cargo's relocation to AAS Southeast to provide redundancy to the Kaagbaantunnel. The minimum separation time $S$ between two vehicles at an intersection node is assumed to be 10 seconds, which ensures a separation of approximately 70 and 40 meters at the maximum travel speed of 25 km/h and 15 km/h. Considering a vehicle carrying six ULDs has a length of 30 meters, this ensures safe operations at both speeds.

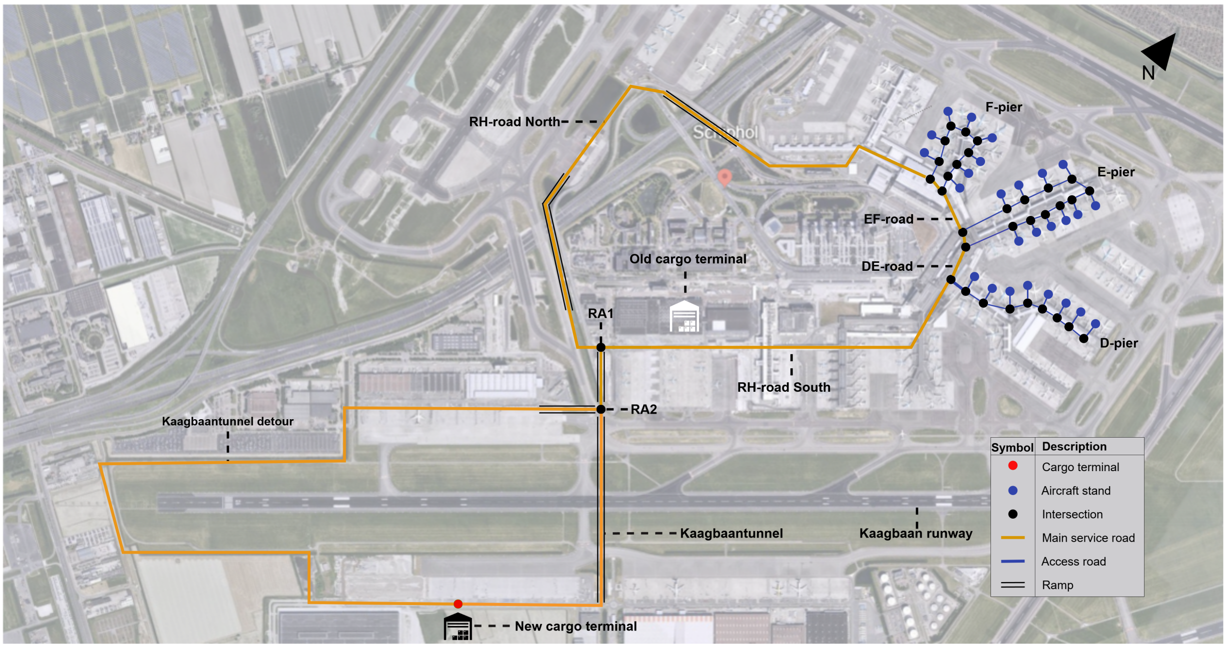

Figure 4: AAS service road graph after KLM Cargo's relocation to AAS Southeast. RA = roundabout

### 4.3 Cargo transportation requests

The cargo transportation request set $R$ for the KLM Cargo case study is based on a combination of KLM Cargo's airside cargo transport data and a synthetic AAS flight schedule for KLM passenger aircraft. KLM Cargo's airside cargo transport data provides the Tonnes of belly cargo transported according to commodity type and transportation flow by KLM cargo was available for 2022. To convert cargo Tonnes to a number of ULDs, it is estimated that on average $X$ (dummy value $X$ for confidentiality) Tonnes of Cargo are packed onto a ULD carried by passenger aircraft. The express commodity is handled as an exemption as this usually entails mail, which is small and lightweight. However, an entire ULD (baggage cart) is generally used to transport this across airside. To account for this, it is assumed that an average express ULD weighs Y kg (dummy value $Y$ for confidentiality). Using this, the average number of ULDs according to commodity type and transportation process are calculated and summarized in table 5.

Table 5: Average ULDs per day according to transportation flow and commodity type. For confidentiality, these values are replaced with dummy values.

| Commodity type | ULDs per day | |
|---|---|---|
| | Inbound | Outbound |
| **General** | 180 | 290 |
| **Express** | 95 | 130 |
| **Secure** | 45 | 60 |
| **Live** | 25 | 40 |
| **Passive cooled** | 75 | 85 |
| **Active cooled** | 55 | 70 |

A flight schedule for KLM passenger-cargo combination flights is synthesized for an average day in 2022 to align with the same year as the airside cargo transportation data used. Based on flight data from AAS [Royal Schiphol Group, ] and CBS [StatLine, ], April 2022 represents an average month of 2022 with approximately 119 daily intercontinental KLM flights. Moreover, given the 2022 KLM cargo data, KLM passenger-cargo combination flights carried an average of Z ULDs in 2022 (dummy value $Z$ for confidentiality). Accordingly, considering this average ULDs per flight and the average number of daily ULDs, 76 out of the 119 international KLM flights carry ULDs. All these 76 intercontinental KLM flights are assumed to be by wide-body aircraft. Next, the flight schedule is synthesized for these 76 intercontinental KLM flights. All flights arrive and depart between 6 AM and 10 PM, concentrating their arrivals and departures into seven waves [Vos, 2019]. This is a typical flight schedule pattern for airlines' operation at their hub airport as it allows short connections between flights. In the KLM operation at AAS, there are seven peaks for intercontinental flights throughout the day.

All 76 wide-body flights are assigned a random arrival time within one of the seven peaks and depart after their turnaround time of approximately 1.5 to 2 hours. The exact turnaround time is randomly assigned. Moreover, the aircraft stand at which a flight is parked is also randomly assigned to a flight while satisfying that no other aircraft is parked at that stand during its turnaround time. This last constraint, together with the limited number of aircraft stands, means that even though the flights get randomly assigned to an arrival time, the flights are spread out throughout the day. Next, the daily ULDs are randomly assigned to the total of 76 KLM cargo flights while satisfying the constraints that each flight gets at least one ULD, at most ten ULDs, and at least four flights have 10 ULDs. The latter flights imitate fully packed cargo flights to other cargo hubs.

Each flight in the synthesized flight schedule carries inbound cargo when it arrives at AAS and outbound cargo when it departs. Inbound cargo generates transportation requests with the aircraft stand as the origin and the cargo terminal as the destination. Conversely, outbound cargo generates transportation requests from the cargo terminal to the aircraft stand of the corresponding flight. Requests are separated according to commodity type.

All commodity types have the same time windows for inbound cargo, while the time windows for outbound cargo vary among commodity types. These time windows are summarized in Table 6 and are based on KLM Cargo's process flows and KLM Ground Services Ground Operations Manual. In addition, it is assumed that one-fourth of the outbound General cargo is ready to be transported across airside before its earliest pick-up time window. For these one-fourths of the outbound General cargo, the earliest pick-up time is randomly assigned between 300 and 200 minutes (dummy values for confidentiality).

Multiple ULDs of the same commodity type destined or originating from the same aircraft are consolidated into one transportation request, which obliges the model to transport them together. If the number of ULDs of a request exceeds the maximum vehicle capacity of six, the request must be divided into two.

The cargo transportation request data consists of the following information per transportation request: *flight number*, *flight's arrival/departure time*, *request number*, *request origin*, *request destination*, *commodity type*, *number of ULDs*, *time window origin*, and *time window destination*.

Table 6: Pick-up and delivery time windows in minutes, categorized by transportation flow and commodity type. * = One-fourth of the outbound General cargo is ready for early transport. For confidentiality, these values are replaced with dummy values.

| **Flow** | **Commodity Type** | $\boldsymbol{\alpha_r^{\text{pick-up}}}$ | $\boldsymbol{\beta_r^{\text{pick-up}}}$ | $\boldsymbol{\alpha_r^{\text{delivery}}}$ | $\boldsymbol{\beta_r^{\text{delivery}}}$ |
|---|---|---|---|---|---|
| **Outbound** | **General cargo** | 200* | 100 | - | 60 |
| | **Express** | 90 | 50 | - | 40 |
| | **Other** | 170 | 100 | - | 50 |
| **Inbound** | **All** | 15 | 120 | - | 180 |

## 4.4 Delay factors

As mentioned before, travel speed decreases if traffic flows increase, resulting in increased travel times. The factor between the increased travel time and the minimum travel time of an arc is the arc's delay factor. This delay factor of an arc depends on the location of an arc in the network and the time period $\tau$ during which the arc is traveled, making the delay factor arc-specific and time-dependent. As mentioned before, the arrival and departure of KLM flights are concentrated into seven peaks throughout the day at AAS to enable short connections between flights. As the wide-body turnaround times are longer, wide-body peaks enclose the narrow-body peaks to allow passenger transfers between narrow-body and wide-body aircraft while minimizing the ground time of an aircraft to its turnaround time. As a consequence, a high number of aircraft are simultaneously at the airport requiring ground handling for their turnaround. This generates high traffic flows of ground-handling vehicles.

The delay factor of the RH-road South and the DE-road is predominantly generated by the traffic flow of ground-handling vehicles for narrow-body aircraft turnaround. In contrast, the delay factor of the EF-road is generated by the traffic flow of ground-handling vehicles for wide-body aircraft turnaround. Accordingly, the traffic flow of these ground-handling vehicles is driven by the demand for aircraft turnaround based on the narrow-body and wide-body flight schedules, respectively. The delay factors of the RH-road North and the Kaagbaantunnel detour are 1, equal to no delay, regardless of the time period $\tau$. When the Kaagbaantunnel is open, its delay factor is set to 1. However, when it is closed, a large delay factor is assigned, making the detour around the Kaagbaantunnel a substantially shorter alternative.

The time-dependent travel time of an arc is calculated by multiplying the minimum travel time of that arc by the arc's delay factor of the time period $\tau$ at which the arc is traveled. On the narrow-body and wide-body arc, delay factors on the interval of [1, 2] and [1, 1.65] apply, respectively. Accordingly, the travel speed intervals in km/h are [25, 12.5] for narrow-body arc and [25, 15.2] for wide-body arc. This narrow-body delay interval is greater compared to the wide-body interval, as a narrow-body peak consists of more aircraft resulting in a higher number of required ground-handling vehicles on the service roads.

The delay factor throughout the day is primarily driven by narrow-body aircraft turnaround demand for the RH-road South and the DE-road, while wide-body aircraft turnaround demand drives the EF-road delay factors. Therefore, these delay factors can be estimated by determining the number of aircraft of each type on the ground simultaneously, based on a synthesized flight schedule. Based on the same April 2022 data, the average daily flights are 916 continental flights and 198 intercontinental flights. It is assumed that all continental flights were narrow-body aircraft and all intercontinental flights were wide-body aircraft. Again, the flights arriving and departing between 6 AM and 10 PM are concentrated into seven waves, with the narrow-body peaks nested into the wide-body peaks, except for the first inbound wave and the last outbound wave. The average turnaround time of wide-body aircraft remains between 1.5 to 2 hours, while for narrow-body aircraft, this is assumed to be between 45 minutes and 75 minutes.

Using the synthesized flight schedule, the number of aircraft on the ground during any time period $\tau$ according to aircraft type ($A$), either narrow-body or wide-body aircraft, is calculated. This is used as input for the delay factors according to aircraft type. The lowest and highest delay factors for each aircraft type are assigned to the time periods with the minimum ($\text{count}_{min}(A)$) and maximum number of aircraft ($\text{count}_{max}(A)$) on the ground of the aircraft type, respectively. For all other time periods, the delay factor is calculated based on the ratio of the aircraft type count for that time period $\tau$ to the minimum and maximum counts using the following formula:

$$\text{delay factor}(A, \tau) = 1 + \frac{\text{count}(A, \tau) - \text{count}_{max}(A)}{\text{count}_{min}(A) - \text{count}(A, \tau)} \tag{34}$$

### 4.5 Instances

An instance refers to an input data set defining a single day of KLM cargo's airside cargo transportation at AAS. It consists of a graph, cargo transportation request, and delay factors. The performance of each strategy is evaluated over multiple operational days, each represented by a distinct instance. To ensure robustness and avoid bias from any single day, results are averaged across these instances. This approach enhances the validity and generalizability of the results. Although the instances vary, they share key similarities that allow results to be averaged across them. Subsequently, the graph, number of flights, number of ULDs per commodity type, commodity pick-up and delivery time windows, and seven-wave structure are similar between instances. The tunnel closes for one time period $\tau$ once during every instance.

The difference between instances is found in the randomly assigned parameters: gate assignment of a flight, arrival time of flight, departure time of flight (based on turnaround time), ULD assignment to flight, and time period during which the tunnel closes. The number of problem instances required for reliable data for the KPIs is determined based on the convergence of the coefficient of variation. The coefficient of variation (CV) measures the dispersion around the mean. The CV is based on the objective function of the ACTP, which is the total travel time. As the number of instances increases, the CV is expected to converge, indicating a reduced variability among the results. Sufficient instances have been included to ensure robust and reliable data for evaluating results.

## 5 Results

Relocating the cargo terminal to Schiphol Southeast provides the opportunity to revise KLM Cargo's operating procedures, both outside and inside the cargo terminal. The ACTP allows a top-view analysis of the effect of different network and terminal strategies on KLM Cargo's airside cargo transportation at AAS. The various strategies are based on the different perspectives on airside cargo transportation by KLM Cargo, AAS, and AirportCreators. The baseline strategy is introduced first in Subsection 5.1, followed by the results of the two strategy levels: the network-level in Subsection 5.2 and the terminal-level in Subsection 5.3.

All results are obtained with Gurobi 11.0.3 using a laptop (AMD Ryzen 5 PRO 6650U 2.90 GHz, 16 GB RAM) under Windows 11 Pro. Python was used to define the models. The results are obtained by setting the model and rolling horizon settings that resulted from a trade-off between the objective function value and computational time on small test instances. These parameter values are $C_{max} = 4$, $S_{max} = 3$, $\Delta t = 20$, and $f = 1$. Solving subproblems with a high number of transportation requests to optimality remains computationally heavy, for which an additional measure is taken: after reaching a time limit of 500 seconds, an optimality gap condition of 0.1 is provided to the solver. In addition, a new time limit is set to 1000 seconds. Accordingly, solving the subproblem cannot take longer than 1500 seconds. However, the computational time of Algorithm 1 remains unlimited, while it increases significantly by the number of requests in a subproblem formulation (as described in Subsection 3.2). As a result, this algorithm becomes the bottleneck of subproblems with a high number of requests.

### 5.1 Baseline

The baseline represents KLM Cargo's current belly cargo transportation and terminal operations with the KLM Cargo terminal relocated to AAS Southeast, serving as a standard against which the effectiveness of alternative strategies can be measured. This baseline was also used during model validation using a graph representation of the AAS network before KLM Cargo's relocation to Southeast. As this baseline is validated, it ensures that the evaluation of results is grounded in a realistic operational context, highlighting the added value of various strategies compared to existing practices. The number of problem instances required for a stabilized CV is based on this baseline and converges after five problem instances. Accordingly, the results of all strategies will be based on the averages across five problem instances.

## 5.2 Network-level strategies

The network-level strategies aim to use the network capacity more effectively. This capacity is based on the capacity of the roads within the network, which is defined as the maximum traffic flow that a certain road can accommodate during a specific time period [Greenshields et al., 1935]. Network capacity is affected by vehicle distribution in the network throughout space and time [Sun et al., 2014]. This distribution can be mitigated through two network-level strategies. Subsubsection 5.2.1 and Subsubsection 5.2.2 describe the spatial distribution and traffic prediction strategy, respectively. Subsequently, the results of both strategies are presented in Subsubsection 5.2.3, after which the results are discussed in Subsubsection 5.2.4.

### 5.2.1 Spatial Distribution Strategy

The distribution of vehicles across the network affects the network's capacity. In the AAS network, two roads connect the cargo terminal with the RA2 node on the opposite side of the Kaagbaan, as shown in Figure 4. Under normal conditions - without Kaagbaantunnel closure - it is evident that the Kaagbaantunnel road offers the shortest travel distance and time. Following the relocation of KLM Cargo to Schiphol Southeast, the Kaagbaantunnel will primarily be used by vehicles transporting cargo. For paths between the RA1 node and the piers, the RH-road South road offers a shorter travel distance than the RH-road North road. However, unlike the Kaagbaantunnel, the RH-road South's capacity is largely occupied by ground-handling vehicles involved in the aircraft turnaround. Accordingly, the delay factors on the RH-road South, DE-road, and EF-road determine which path between the RA1 node and piers results in the shorter travel time.

As the problem optimizes the total travel time, vehicles are assigned to paths using arcs with the shortest travel times. This results in higher traffic flows on arcs with shorter travel times and underutilized arcs with longer travel times. In addition, high utilization of the Kaagbaantunnel increases the risk of a tunnel closure, due to the increased risk of vehicle failure or dropped cargo, which would result in all vehicles having to use the longer Kaagbaantunnel detour instead. This risk can be mitigated by reducing the utilization of the Kaagbaantunnel. To address this imbalance and mitigate the risk of tunnel closure, the proposed strategy aims to better distribute cargo vehicles across the network by increasing the use of underutilized arcs. The aim is to alleviate traffic flow on the Kaagbaantunnel, RH-road South, DE-road, and EF-road arcs. As a result, vehicles are expected to be distributed more evenly throughout the network, improving the flow on main service road arcs significantly.

To achieve this, vehicles transporting General cargo are obliged to take the Kaagbaantunnel detour arc instead of the Kaagbaantunnel arc, which is roughly half of the ULDs. Similarly, General cargo originating from and destined for the F-pier is assigned to RH-road North instead of using the RH-road South, DE-road, and EF-road. This additional transportation requirement for General cargo is implemented in Algorithm 1. In line 10, a subset of set $P_c$ is obtained such that all General cargo can only be transported by the obliged paths. It is expected that this strategy will lead to improved vehicle distribution but longer total and average vehicle travel times and distances compared to the baseline.

### 5.2.2 Traffic Prediction Strategy

The network capacity is also affected by the distribution of vehicles over time, as high traffic flows during the same period reduce travel speeds, leading to increased travel times. As mentioned before, the traffic flows at AAS at the RH-road South, DE-road, and EF-raod are heavily influenced by flight schedules, as ground handling vehicle activity peak around aircraft turnaround times. As aircraft arrivals and departures are concentrated into seven peaks throughout the day at AAS, similar peaks are observed in ground handling traffic flows. To improve vehicle distribution over time, the traffic prediction strategy is evaluated. This strategy aims to incentivize the traveling of the cargo vehicles during time periods with the lowest traffic flows of other ground handling vehicles by taking into account the current and future traffic conditions.

The implementation of this strategy requires constraints 27, 28, and 29 of the subproblem formulation to change. Two additional binary decision variables are introduced to formulate the additional constraints linearly. This linear formulation improves the computational efficiency of the resulting model. These constraints are detailed in Table 7.

Table 7: Mathematical notation of additional decision variables for the Traffic Prediction Strategy.

| Notation | Description |
|---|---|
| $b^{p\tau}_{kvw}$ | $= 1$ if vehicle $k$ travels from node $v$ to node $w$ of path $p$ during current horizon $H_\tau$, $= 0$ otherwise |
| $b^{pf}_{kvw}$ | $= 1$ if vehicle $k$ travels from node $v$ to node $w$ of path $p$ during forward horizon $H_f$, $= 0$ otherwise |

Five constraints are included in the subproblem formulation to define $b^{p\tau}_{kvw}$ and $b^{pf}_{kvw}$. These constraints are:

$$t^p_{kv} \leq \beta_{H_\tau} + M * (1 - b^{p\tau}_{kvw}) \qquad \forall k \in K, p \in P, (v,w) \in A^p \quad (35)$$

$$t^p_{kv} > \beta_{H_\tau} - M * (1 - b^{pf}_{kvw}) \qquad \forall k \in K, p \in P, (v,w) \in A^p \quad (36)$$

$$b^{p\tau}_{kvw} + b^{pf}_{kvw} = x^p_k \qquad \forall k \in K, p \in P, (v,w) \in A^p \quad (37)$$

$$b^{p\tau}_{kvw} \leq x^p_k \qquad \forall k \in K, p \in P, (v,w) \in A^p \quad (38)$$

$$b^{pf}_{kvw} \leq x^p_k \qquad \forall k \in K, p \in P, (v,w) \in A^p \quad (39)$$

Accordingly, the subproblem's travel time constraints 27, 28, and 29 are reformulated to include these new decision variables. This new formulation, presented below, considers the influence of the delay factor during the current horizon $H_\tau$ and the forward horizon $H_f$ on the travel time of the arcs.

$$t^p_{kw} - t^p_{kv} = TT_{vw} * (D^\tau_{vw} * b^{p\tau}_{kvw} + D^f_{vw} * b^{pf}_{kvw}) \qquad \forall k \in K_n, p \in P, (v,w) \in A^p_m \quad (40)$$

$$t^p_{kw} - t^p_{kv} \geq H/2 + TT_{vw} * (D^\tau_{vw} * b^{p\tau}_{kvw} + D^f_{vw} * b^{pf}_{kvw}) \qquad \forall k \in K_n, p \in P, (v,w) \in A^p_a \quad (41)$$

$$t^p_{kw} - t^p_{kv} \geq TT_{vw} * (D^\tau_{vw} * b^{p\tau}_{kvw} + D^f_{vw} * b^{pf}_{kvw}) + \delta_t * T \qquad \forall (k,c,p) \in F, (v,w) \in A^p \quad (42)$$

This strategy's advantage lies in considering the arcs' current and future traffic conditions. By incorporating this information, it is expected that the model makes better-informed scheduling decisions about when to transport cargo. Subsequently, the total travel time of all vehicles is expected to improve compared to the baseline strategy.

### 5.2.3 Results of network-level strategies

Table 8 presents the network-level strategies results compared with the baseline. Figure 5 visualizes the distribution of the cargo vehicles throughout the day and Figure 6 visualizes the spatial distribution of the vehicles.

Table 8: KPIs for network-level strategies. SD = Spatial Distribution, TP = Traffic Prediction, ATL = Average ULD Train Length, TT = Travel Time, TD = Travel Distance.

| | Vehicle Utilization | | Total Routing | | Average Vehicle Routing | |
|---|---|---|---|---|---|---|
| **Strategy** | **Vehicles [#]** | **ATL [# ULD]** | **TT [h]** | **TD [km]** | **TT [min]** | **TD [km]** |
| **Baseline** | 127 | 2.93 | 64.7 | 958.0 | 30.5 | 7.5 |
| **SD** | 126 (-0.94%) | 2.95 (+0.68%) | 73.4 (+13.49%) | 1230.3 (+28.42) | 35.0 (+14.71%) | 9.8 (+30.30%) |
| **TP** | 133 (+5.98%) | 2.80 (-4.40%) | 66.4 (+ 3.79%) | 978.3 (+3.03 %) | 30.0 (-2.10%) | 7.4 (-2.83%) |

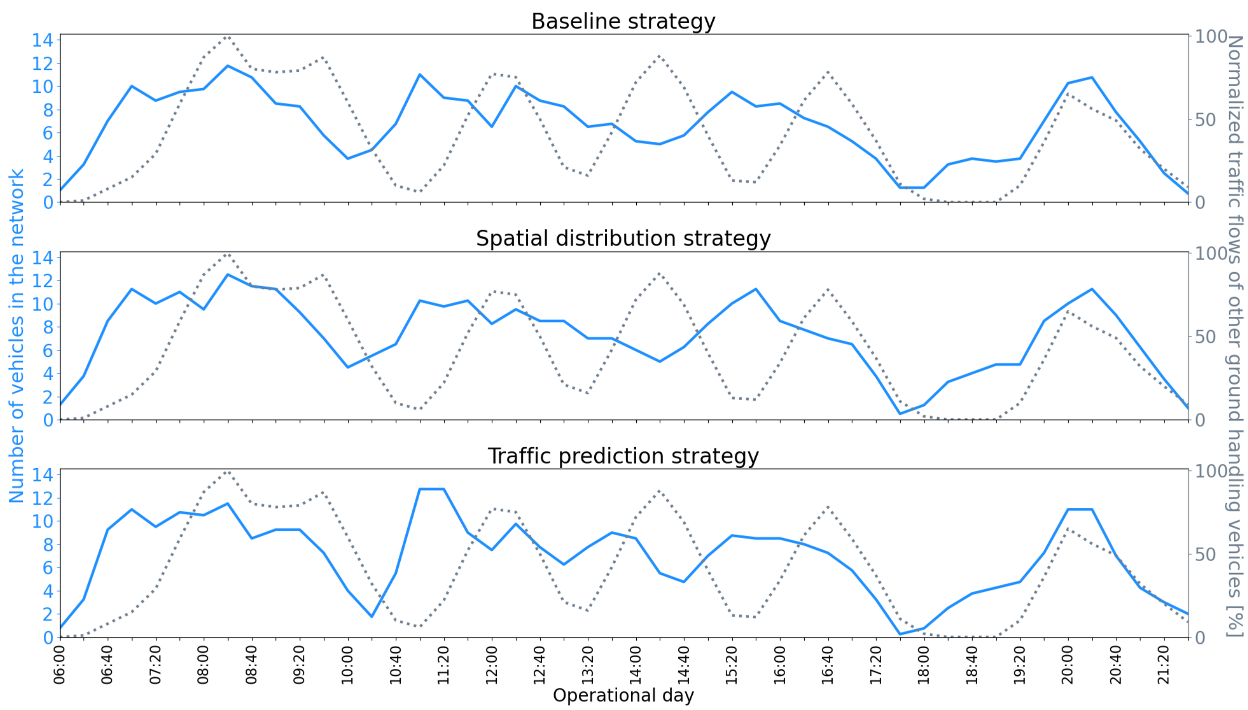


Figure 5: Vehicles en route in the network for the network-level strategies with traffic flow indications of others throughout the operational day.

For the spatial distribution strategy, it is observed that the number of vehicles slightly reduces, increasing the average ULD train length a little. As expected, the total and average travel time and distance increase substantially as vehicles carrying General cargo are obliged to take the longer detour roads. The percentage increase in travel distance is roughly twice that of travel time for both total and average vehicle routing. This indicates an increase in travel with higher speeds, which may result from traveling arcs without delay factors (such as the Kaagbaantunnel detour and the RH-road North) or traveling during time periods with lower delay factors. Figure 5 shows that the latter is not the case, as the distribution of cargo vehicles throughout the day remains approximately the same during both peak and off-peak traffic periods of other ground vehicles compared to the baseline. Additionally, the figure indicates an overall increase in the number of vehicles in the network throughout the day. This rise is attributed to the increased average travel time, causing vehicles to remain in the network for longer durations. Figure 6 shows that the distribution of vehicles between the Kaagbaantunnel arc and the Kaagbaantunnel detour arc substantially improves compared to the baseline. In contrast, only a slight increase in distribution is observed between the RH-road South and RH-road North.

For the traffic prediction strategy, it is observed that the number of vehicles increases significantly, decreasing the ULD train length. Accordingly, the total travel time and distance increase, while the vehicle average travel time and distance decrease. These results suggest an decrease in the average number of requests fulfilled by a vehicle (Figure 8 in Appendix A). Accordingly, vehicles need to visit fewer aircraft stands on their paths, making the average paths shorter (Figure 7 in Appendix A). Figure 5 shows that the distribution of vehicles throughout the peak and off-peak periods of other ground handling vehicles improves. For instance, it is observed that during 06:00-07:00 and 10:40-11:40, the number of vehicles in the network increased during the off-peak of the other ground handling vehicles. This improvement is also reflected in the higher increase in average vehicle distance compared to time, suggesting higher travel speed compared to the baseline. Besides, the vehicle distribution throughout the network slightly degrades compared with the baseline as can be seen in Figure 6.

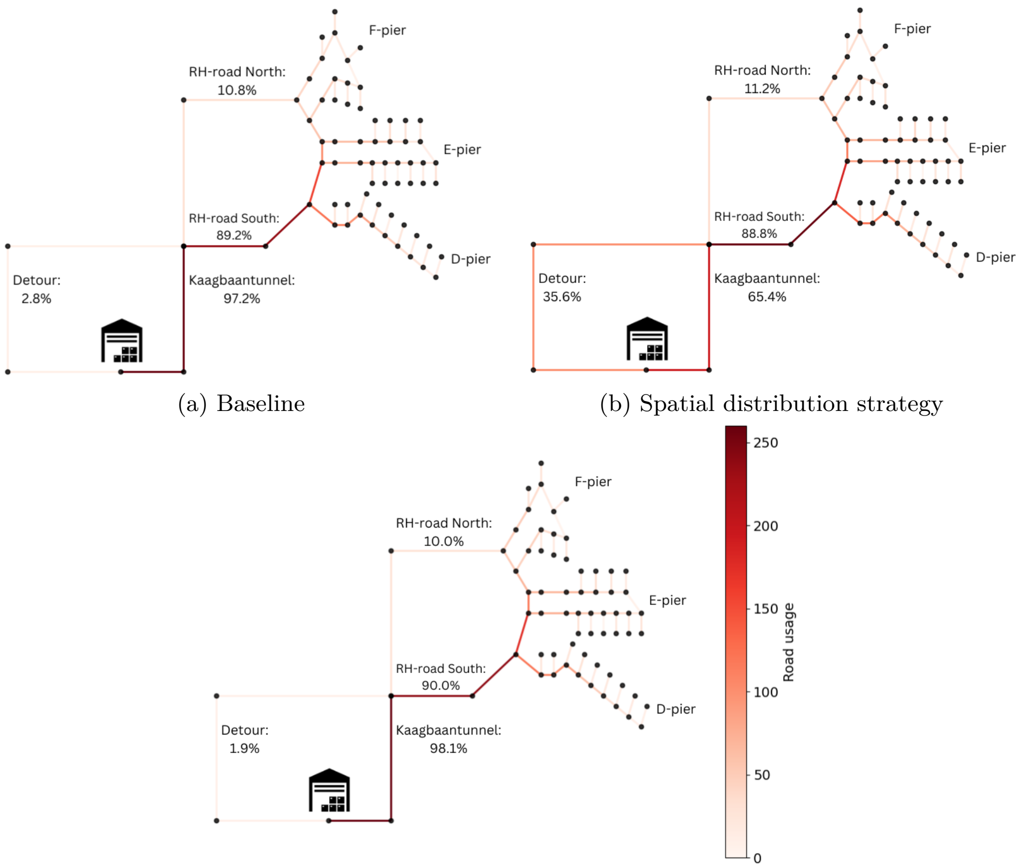

Figure 6: Spatial distribution of vehicles across the network for the terminal-level strategies.

#### 5.2.4 Discussion of network-level strategies

The spatial distribution strategy performance degrades compared with the baseline on the total and vehicle average route performance, while the vehicle utilization slightly increases. The distribution of vehicles throughout time degrades as vehicles remain in the network for a longer duration. Accordingly, this strategy only improves cargo transportation in terms of its intended performance field: spatial vehicle distribution throughout the network. Although only a substantial improvement in spatial distribution is found between the Kaagbaantunnel and the Kaagbaantunnel detour, only a slight improvement is observed between the RH-road South and North.

This strategy is not appealing for AAS as vehicle distribution through time decreases. In addition, the benefits of spatial distribution are minor for AAS, as their main interest in spatial distribution is to reduce the use of the already busy RH-road South, DE-road, and EF-road. The spatial vehicle distribution between the Kaagbaantunnel and its detour is substantial, mitigating the risk of tunnel closure which is important for KLM Cargo's transportation. Although that does not outweigh the significant total routing degradation increasing the operational costs of the transport for KLM Cargo. In addition, it indicates that an additional nine travel time hours are required per operational day, necessitating more manpower, which undesirable for KLM Cargo.

The results of the traffic prediction strategy do not align with the expectations. It was expected that the total and average routing performance would improve, making this strategy appealing to both KLM Cargo and AAS. However, the results indicate the opposite: both vehicle utilization and total routing performance degrades. These deviations from the expectations are likely due to the increased model complexity of this strategy. As a result, the optimization of multiple subproblems terminated after the predefined time limit of 1500 seconds with substantial optimality gaps up to 80%, affecting the solution quality. In contrast, the baseline and spatial distribution strategy solved most of these subproblems with an optimality gap of 10% or even optimality. Consequently, it cannot be proven that the results of the traffic prediction strategy are directly comparable with those of the baseline and spatial distribution strategies.

## 5.3 Terminal-level strategies

It is of interest to KLM Cargo to evaluate the effect of various terminal operational concepts on airside cargo transportation. The terminal-level strategies are derived from two potential operational concepts for the cargo terminal and their respective impacts on airside cargo transportation: pull and push. Subsubsection 5.3.1 and Subsubsection 5.3.2 explain the pull and push strategy, respectively. Accordingly, the results of both strategies are presented in Subsubsection 5.3.3, after which the results are discussed in Subsubsection in 5.3.4.

### 5.3.1 Pull Strategy

The pull strategy schedules outbound cargo transport so that cargo arrives at the aircraft stand just in time for loading onto the aircraft. This requires transportation of the outbound cargo to be triggered by the aircraft's loading time, which is defined in the ACTP model as the delivery deadline at the aircraft stand ($\beta_r^{delivery}$). This strategy prevents cargo from being parked for a long time at the aircraft stand before loading, increasing the aircraft stand's safety and orderliness. It requires cargo to be stored at the cargo terminal for longer times, increasing the required terminal storage capacity. An advantage of this strategy is that cargo with short connecting times at the cargo terminal can be added to already stored ULDs with remaining available capacity. This approach aligns well with KLM Cargo's hub operations, where providing short cargo connecting times is part of the profit model. The pull strategy is implemented by narrowing the delivery time window for outbound cargo to 15 minutes before the cargo's delivery deadline at the aircraft stand. The pick-up and delivery time windows for this strategy are given in Table 9.

Despite these benefits, the pull strategy introduces certain risks in the real-life application. Since cargo is transported later, the on-time performance of outbound cargo becomes vulnerable to traffic conditions. High transport delays can result in cargo arriving late, making this strategy riskier in unpredictable airside road traffic scenarios. This could result in cargo not making it to the flight and being rescheduled onto a later flight having financial consequences.

Table 9: Pick-up and delivery time windows for the pull strategy, categorized by transportation flow and commodity type, with deviations from the baseline strategy highlighted in bold. For confidentiality, these values are replaced with dummy values.

| Flow | Commodity Type | $\alpha_r^{\text{pick-up}}$ | $\beta_r^{\text{pick-up}}$ | $\alpha_r^{\text{delivery}}$ | $\beta_r^{\text{delivery}}$ |
|---|---|---|---|---|---|
| **Outbound** | **General cargo** | **105** | - | **75** | 60 |
| | **Express** | **85** | - | **55** | 40 |
| | **Other** | **95** | - | **65** | 50 |
| **Inbound** | **All** | 15 | 120 | - | 180 |

### 5.3.2 Push strategy

The push strategy involves transporting outbound cargo across airside immediately after it has been built up in ULDs at the cargo terminal. This ensures that cargo reaches the aircraft stand well before loading begins, reducing susceptibility to traffic conditions and enhancing overall reliability. Additionally, the required storage capacity at the cargo terminal decreases. Instead, the cargo is stored at the aircraft stand for longer periods of time, decreasing safety and orderliness. The push strategy is implemented by narrowing the outbound cargo's pick-up time window to 15 minutes after the earliest cargo pick-up time. The pick-up and delivery time windows implemented for the push strategy are presented in Table 10. As the cargo departs from the cargo terminal well ahead of flight departure, the on-time arrival of the cargo at the aircraft stand is less vulnerable to traffic conditions.

Table 10: Pick-up and delivery time windows for the push strategy, categorized by transportation flow and commodity type, with deviations from the baseline strategy highlighted in bold. * = One-fourth of the outbound General is ready for early transport. For confidentiality, these values are replaced with dummy values.

| Flow | Commodity Type | $\alpha_r^{\text{pick-up}}$ | $\beta_r^{\text{pick-up}}$ | $\alpha_r^{\text{delivery}}$ | $\beta_r^{\text{delivery}}$ |
|---|---|---|---|---|---|
| **Outbound** | **General cargo** | 200* | **185** | - | 60 |
| | **Express** | 90 | **75** | - | 40 |
| | **Other** | 170 | **155** | - | 50 |
| **Inbound** | **All** | 15 | 120 | - | 180 |

### 5.3.3 Results of terminal-level strategies

Table 11 presents the terminal-level strategies results compared with the baseline. Figure 7 visualizes the distribution of the cargo vehicles throughout the day.

Table 11: KPIs for terminal-level strategies. ATL = Average ULD Train Length, TT = Travel Time, TD = Travel Distance.

| | **Vehicle Utilization** | | **Total Routing** | | **Average Vehicle Routing** | |
|---|---|---|---|---|---|---|
| **Strategy** | **Vehicles [#]** | **ATL [# ULD]** | **TT [h]** | **TD [km]** | **TT [min]** | **TD [km]** |
| **Baseline** | 127 | 2.93 | 64.7 | 958.0 | 30.5 | 7.5 |
| **Pull** | 120 (- 5.51%) | 3.09 (+5.51%) | 63.8 (- 1.33%) | 927.7 (- 3.17%) | 31.8 (+4.20%) | 7.7 (+2.23%) |
| **Push** | 128 (+0.79%) | 2.91 (- 1.55%) | 66.1 (+2.20%) | 977.7 (+2.05%) | 30.9 (+1.37%) | 7.6 (+1.20%) |

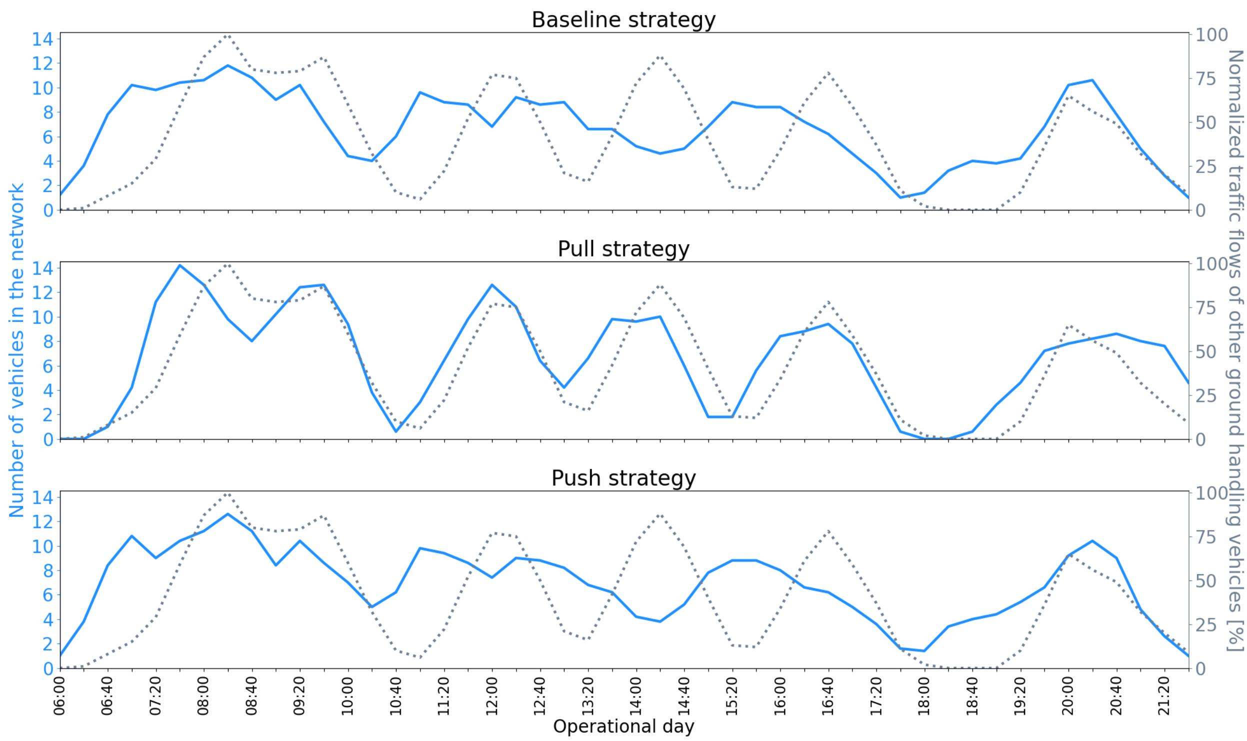


Figure 7: Vehicles en route in the network for the terminal-level strategies with traffic flow indications of other ground handling vehicles throughout the operational day.

For the pull strategy, it noted that the number of vehicles is reduced leading to increased average ULD train length. Accordingly, the total travel time and distance decrease, while the average vehicle travel time and distance increase. These results imply that the average requests transported per vehicle increase, resulting in on average longer paths to pick up and deliver all requests (substantiated by Figure 10 and Figure 11 in Appendix A). The difference between the percentage increase in vehicle average travel time and distance indicates that the average travel speeds decrease, suggesting increased travel during periods with higher delay factors. This is substantiated by Figure 7, which visualizes that the distribution of cargo vehicles over time coincides more with that of other ground handling vehicles compared to the baseline. Additionally, the figure indicates that the distribution of vehicles is concentrated more into peaks compared to the baseline.

For the push strategy, the number of vehicles slightly increases resulting in shorter average ULD train lengths. The total and vehicle average travel time and distance increase. This implies that the average number of requests per vehicle reduces while the average path length to fulfill these requests increases (substantiated by Figure 10 and Figure 11 in Appendix A).

Moreover, it is observed that the percentage increase in travel time and distance is approximately equal for both total routing and vehicle average routing. This suggests approximately similar travel speeds compared to the baseline, indicating that vehicles operate during time periods with comparable delay factors. This is also observed in Figure 7, where the distribution of vehicles over time closely resembles that of the baseline. In addition, the figure indicates. Additionally, the figure shows a slight increase in the number of vehicles in the network throughout the day, as a result of the increased number of vehicles required and the increase in average vehicle travel time.

#### 5.3.4 Discussion of terminal-level strategies

The pull strategy substantially improves the vehicle utilization and the total routing performance, which is compromised by the increase in average vehicle routing performance. The distribution of vehicles throughout time degrades as cargo vehicle activity becomes more concentrated into peaks. In addition, these peaks increasingly align with the peak activity of other ground-handling vehicles, leading to higher delay factors. This results from the increased overlap of the pull strategy's outbound cargo delivery time windows (as presented in 9) with the narrow- and wide-body turnaround peaks, during which ground handling vehicle traffic causes significant delays.

This strategy benefits KLM Cargo as it improves operational costs due to improved vehicle utilization and reduced vehicle total routing performance. Additionally, fewer manhours are theoretically required due to a reduction in total travel time. However, the actual impact on manhours depends on how the vehicle paths are assigned to drivers. This is at the cost of increasing terminal storage capacity. During the KLM Cargo terminal design phase, it should be evaluated whether these airside cargo transportation improvements outweigh the costs of increasing the terminal's storage capacity. AAS benefits from this strategy as the number of vehicles in the network reduces as well as the total time spend in the network. However, these advantages are offset by the drawback of increased vehicle movements during periods with high delay factors, pushing traffic flows closer to the network's capacity.

The results of the push strategy degrade the vehicle utilization and total and average vehicle routing performance. The vehicle distribution throughout time slightly degrades as the number of vehicles in the network increases as well as their average time spend in the network.

This strategy is not beneficial for KLM Cargo as the operational costs increase, including the required manhours. The only positive aspect of this strategy would be the reduction in storage capacity at the cargo terminal. Similar to the pull strategy, it should be determined during the new KLM Cargo terminal design phase whether the reduced storage capacity required for this strategy outweighs the airside cargo transportation degradation. This strategy is not beneficial for AAS, as it slightly decreases the vehicle distribution throughout the day.

## 6 Conclusions and future research

This paper proposes the first MIP formulation for the airside transportation of cargo ULDs between passenger aircraft and cargo terminals, considering vehicle capacity utilization, cargo commodity differentiation, and time-dependent travel times on the airport's service roads. A rolling horizon-based heuristic is applied, making the problem formulation linear and computationally feasible. This model was applied to a case study of the potential relocation of KLM Cargo's terminal at Amsterdam Airport Schiphol (AAS) to a new site. This relocation provides the opportunity to evaluate the effect of various strategies, for the network usage and the new cargo terminal's operating procedures, on airside cargo transportation. Subsequently, the aim of this paper is to determine whether there are network-level and terminal-level strategies that can optimize the airside belly cargo transport between cargo terminals and passenger aircraft across the airport's service roads.

The network-level strategies aim to use the airside road network capacity more effectively, for which two strategies are compared with the baseline strategy, representing business-as-usual airside cargo transportation. The spatial distribution strategy aims to relocate vehicles between over- and underutilized roads, while the traffic prediction strategy aims to incentivize travel during periods with less traffic. These strategies are evaluated based on vehicle utilization (number of vehicles and average ULD train length), total routing performance (total travel time and distance), average vehicle performance (average vehicle travel time and distance), and network distribution (distribution of vehicles across space and time in the network). The spatial distribution strategy degrades the total and vehicle average routing performance of the cargo transportation substantially, against a minor increase in vehicle utilization. The spatial distribution strategy improves the distribution between the

Kaagbaantunnel and its detour road but distributes the vehicles between other over- and underutilized roads less than intended. Accordingly, this slight improvement is outweighed by the significantly degrading average vehicle routing performance, making this strategy beneficial for AAS. Moreover, this strategy is not beneficial for KLM Cargo either, as the total routing performance substantially degrades. Contrary to expectations, the traffic prediction strategy degrades airside cargo transportation performance. This unexpected outcome is likely due to the reduced solution quality caused by the increased model complexity introduced by this strategy. As a result, the optimization is stopped at the predefined time limit with a significantly higher average optimality gap compared to other strategies. Consequently, its cannot be proven that its results are comparable with the results of the baseline and spatial distribution strategy.

The terminal-level strategies evaluate the impact of potential cargo terminal operational concepts on airside cargo transportation to the baseline, for which two strategies are defined: pull and push strategy. These strategies are evaluated on the same aspects as the network-level strategies, except for the spatial distribution. In the pull strategy, outbound cargo is scheduled so that cargo arrives at the aircraft stand just in time for loading onto the aircraft, such that it does not have to be parked at the aircraft stand to await loading. The pull strategy improves the performance of airside cargo transportation in terms of total route performance and vehicle utilization. This is beneficial for KLM Cargo as it reduces operational costs, like manhours and fuel consumption. In addition, AAS also benefits from improved vehicle utilization and total routing performance. However, this does not outweigh the fact that the distribution of cargo vehicles over time significantly coincides with the peak activity of other ground-handling vehicles. This is undesirable for AAS, as the increased cargo vehicle movements during periods of high traffic flow push the network closer to its capacity, leading to delays. In the push strategy, outbound cargo is transported across airside immediately after it has been built up in ULDs at the cargo terminal. This push strategy degrades the performance of airside cargo transportation on all evaluated aspects: vehicle utilization, total and average vehicle routing performance, and vehicle distribution. Hence, this strategy does not optimize the airside cargo transportation and is not beneficial for either KLM Cargo or AAS.

In conclusion, airside belly cargo transportation is optimized on a terminal-level by the pull strategy, while on the network-level the baseline strategy outperforms the suggested strategies.

Next, recommendations for future research are presented, starting by addressing model recommendations followed by strategy-specific recommendations.

A characteristic of the ACTP is that cargo pick-up and delivery must occur within hard time windows, as any delays within the airside belly cargo transportation can lead to financial losses and reduced service quality. A potential direction for future research is to incorporate soft time windows into the problem formulation, allowing for delays that can be penalized within the model. This adjustment would also make the model applicable to full freighter cargo transport, where adherence to flight schedules is less strict compared to belly cargo transportation. Guepet et al. [Guépet et al., 2016] can serve as a reference for incorporating time window deviations into the problem formulation.

Another future research direction is to improve the model's computational efficiency to enable using the model for real-time routing and scheduling of cargo throughout an operational day. Currently, the model is not suitable for continuous operational use, a the compuational time for certain subproblems (with a large size of request set $R$) exceeds the subproblem's planning horizon. This is primarily due to the time required for generation of the request combination set $C$ by Algorithm 1 and solving the subproblem itself. To address this, it is recommended to investigate methods for generating request combination set $C$ more efficiently, avoiding its factorial growth with respect to the request set $R$. Additionally, to improve the subproblem's solving time, implementing a column generation algorithm is suggested to reduce the subproblem's solution space.

In addition, a more efficient generation of the request combination set $C$, as suggested above, would also allow an increase in the size of the request set $R$. This is particularly relevant because the current cargo transportation request set $R$ groups ULDs of the same commodity type, originating from or destined for the same flight, into a single request. As a result, all ULDs within a request must be transported together in one ULD train by the same vehicle. However, if the model's efficiency improved, each ULD could be treated as a separate request, allowing for greater flexibility in consolidating ULDs into ULD trains and improving overall transportation efficiency.

Due to the increased model complexity introduced by the traffic prediction strategy, its solution quality was significantly affected, making it uncertain whether its results are directly comparable to those of the baseline and spatial distribution strategies. To address this, it is recommended to run the baseline and both network-level strategies on smaller instances where the traffic prediction strategy can also generate reliable solutions. This would allow for a meaningful comparison between these strategies and accordingly, improve the conclusion regarding the effectiveness of network-level strategies on airside cargo transportation.

The pull strategy increases the vulnerability of the on-time performance of outbound cargo transportation to traffic conditions, which is not assessed in the ACTP presented in this paper. Therefore, it is recommended to re-evaluate the pull strategy using the ACTP with soft time windows. As mentioned before, Guepet et al. [Guépet et al., 2016] can serve as a reference for incorporating these soft time windows. An ACTP formulation with soft time windows would enable a more comprehensive evaluation of the pull strategy.

In addition, it is recommended to investigate the combination of network-level and terminal-level strategies to improve airside cargo transportation, as at each level a different strategy can be implemented. Furthermore, combinations within strategy levels can also be assessed. One particularly interesting strategy is a hybrid push and pull strategy. Assuming limited storage capacity at the cargo terminal, a pull strategy could be employed as long as storage space is available. Once the storage reaches full capacity, the push strategy would be activated to avoid the need for storage of the cargo at the terminal. As storage capacity becomes available again, the system could revert to the pull strategy.

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# Appendices

Appendix A presents two additional visualizations for the network-level and terminal level, respectively. These figures support the results as presented in Subsubsection 5.2.3 and Subsubsection 5.3.3.

## A Additional results

For the network-level strategies, Figure 8 visualizes the number of requests transported per vehicle and Figure 9 visualizes the number of aircraft stands visited during a vehicle's round trip.

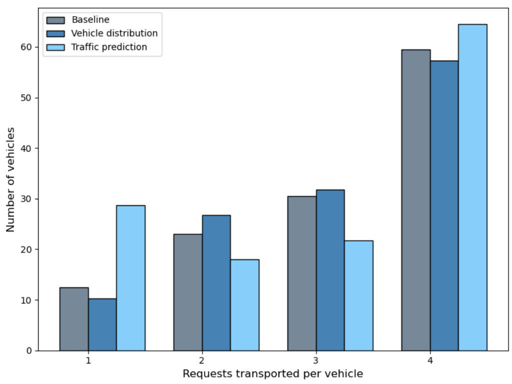



Figure 8: Number of requests transported per vehicle for the network-level strategies

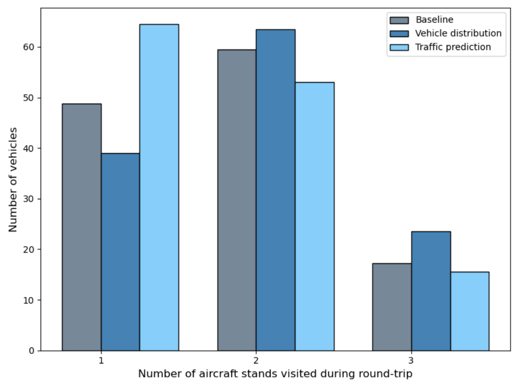



Figure 9: Number of aircraft stands visited during a vehicle's round-trip for the network-level strategies

For the terminal-level strategies, Figure 10 visualizes the number of requests transported per vehicle and Figure 11 visualizes the number of aircraft stands visited during a vehicle's round trip.

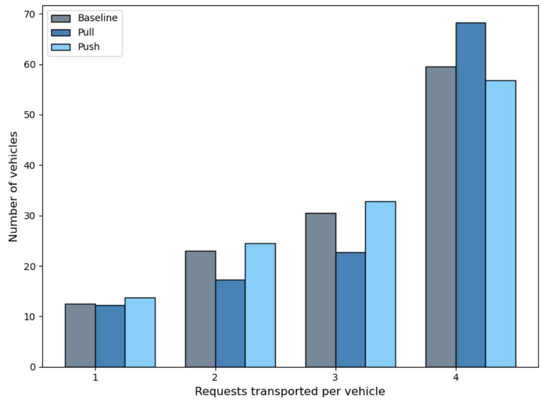



Figure 10: Number of requests transported per vehicle for the terminal-level strategies

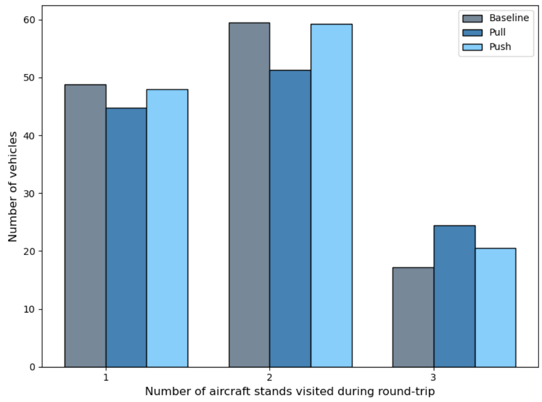



Figure 11: Number of aircraft stands visited during a vehicle's round-trip for the terminal-level strategies

# II

## Literature Study

# 1
# Introduction

This research proposal describes the thesis's conceptual and technical research design. In addition, a literature review is included to substantiate the literature gap that will be filled during the proposed thesis. This chapter gives an introduction to the thesis problem. First, the background of the research problem is described in Section 1.1. Then, the research objective and questions are defined in Section 1.2 and Section 1.3, respectively. The initial research scope is confined in Section 1.4. Finally, an overview of the remaining chapters in this proposal is provided in Section 1.5

## 1.1. Background

To facilitate passenger growth at Schiphol, a new A-pier is currently being constructed on the south side of Schiphol Centre, connected to the B-pier. Correspondingly, a new baggage handling system might be required to accommodate the increase baggage amounts. In addition, the increase passenger growth might require an additional passenger terminal. To accommodate these developments, KLM Cargo's terminals (Vrachtgebouw 1, 2, and 3) must be relocated to make room. The new KLM Cargo Terminal, New Cargo Terminal (NCT), will most likely be located at Schiphol Southeast, on the other side of the Kaagbaan. The Schiphol Southeast area is called CargoCity, as all cargo handlers are consolidating in this area. Other cargo handlers are already located at CargoCity or will move to CargoCity before the NCT is operational. Subsequently, these relocations lead to changes in the airside cargo transportation process.

The airside cargo transportation process focusses on the transportation of cargo between cargo terminals and aircraft. This process can be divided into two flows: import and export. Import cargo arrives by aircraft at an aircraft stand, where it is unloaded onto dollies. Trucks pick up these dollies and transport them to the cargo terminal of the corresponding cargo handler. In the terminal, the cargo is either forwarded to landside transport or transits to the export cargo flow. Export cargo can also arrive at the cargo terminal by landside transport. In the terminal, the export cargo is prepared for flight and loaded onto dollies. These dollies are then transported by truck from the terminal to the aircraft stand of the corresponding flight.

Trucks make use of the airport service roads to perform airside cargo transportation. At Schiphol, other vehicles also use these airport service roads, such as other ground handling vehicles, authority vehicles, (office) suppliers, contractors, and construction workers. The activity of other ground-handling vehicles depends on Schiphol's flight schedule, while the activity of the other vehicles is approximately constant between office hours. On the service roads, the regular traffic regulations apply with some additional restrictions, such as a speed limit of 30 km/u. Generally, the service road's traffic flow does not exceed its capacity. However, the service roads at Schiphol Centre are very busy, especially between the A- and D-pier. Speeds are reduced whenever a service road's traffic flow exceeds its capacity. This implies that service roads are characterized by dynamic travel speeds that depend on traffic flow.

Most cargo handlers at Schiphol transport their cargo by freighter aircraft. Freighter aircraft are parked at freight stands at Schiphol South or Southeast. After the relocation of KLM Cargo to the NCT, most freighter aircraft are expected to be parked at freight stands at Schiphol Southeast. These stands are near the cargo terminals at CargoCity, resulting in short airside cargo transport distances on the service roads. However, KLM Cargo transports approximately 75-80% of its cargo as belly freight in its passenger aircraft's bellies. Some other cargo handlers also transport small amounts of their cargo as belly freight. Passenger aircraft are parked at passenger aircraft stands connected to or close to the passenger terminals and piers at Schiphol Centre. Moving the cargo terminals from Schiphol Centre (or DNATA from Schiphol South) to CargoCity increases the distance between the cargo terminals and the passenger aircraft stands.

The only service road connection between Schiphol Centre or Schiphol South and Schiphol Southeast is a tunnel underneath the Kaagbaan, named the Kaagbaantunnel. Figure 1.1 visualizes this connection between the several Schiphol areas. When KLM Cargo would agree with the relocation to CargoCity, an additional connection is requested between Schiphol Centre and CargoCity to provide redundancy for the Kaagbaantunnel. The additional connection will be a service road around the 06 head of the Kaagbaan. Compared to using the Kaagbaantunnel, this connection will increase the travel time by approximately seven minutes between Schiphol Centre and CargoCity. Therefore, the Kaagbaantunnel is a critical connection for airside belly cargo transportation between the cargo terminals at CargoCity and Schiphol Centre, even with the additional connection in place. Hence, the Kaagbaantunnel's traffic flow, capacity, and reliability are essential for handling belly cargo.


Figure 1.1: Visualization of the Kaagbaantunnel connection between the Schiphol Centre, South and Southeast areas.

The tunnel is perpendicular to the Kaagbaan and has two lanes in opposite directions. The Kaagbaantunnel ends in a roundabout at both ends. The tunnel's capacity is the maximum vehicle throughput within a time interval. According to the Servicemanager Tunnel Safety at Schiphol, theoretical and safety capacities are distinguished. The theoretical capacity is the maximum number of vehicles within a certain time interval that physically limits the tunnel's throughput. Studies performed for Schiphol indicated that the capacity of the roundabouts limits the tunnel's theoretical capacity. Nevertheless, it is not expected that the changing traffic movements due to the move of cargo handlers to CargoCity will reach the capacity limit of these roundabouts. The safety capacity concerns the allowed capacity within a certain time interval to ensure a safe tunnel operation. As the tunnel is longer than 250 meters, the Dutch 'Tunnelwet' applies to it. This Tunnelwet enforces the European Tunnel Directive. The Tunnelwet directly influences the reliability of the tunnel. For example, the Tunnelwet specifies that the tunnel should be closed whenever a vehicle is not moving or if an item is dropped in the tunnel. In such a case, the Schiphol authority has to visit the tunnel, investigate the situation, and solve the problem. Only after the authority gives an all-clear sign will the tunnel be opened again. In addition, some vehicles may have a reduced speed in the tunnel, for instance, due to the combination of the vehicle weight and the tunnel's slope. This results in a moving bottleneck due to the unavailability of space to overtake the slower vehicle.

Currently, all cargo handlers perform their airside cargo transportation separately. In addition, these airside cargo transportations are executed by truck drivers who receive a single task at the time: pick up cargo at the terminal and deliver it to an aircraft stand, or vice versa. Then, when the truck is empty, it returns to its first location to receive a new task. As a result, the truck does not carry any cargo on one way of its journey, which reduces the efficient use of the service road capacity. Besides, the task of a driver can entail dropping off two cargo dollies at an aircraft, even though the truck's maximum capacity is six dollies. Therefore, the carrying capacity of a truck carrying is not fully utilized.

Cargo can be divided into numerous commodities with different handling requirements. This differentiation influences airside cargo transportation operations. Different handling requirements among the commodities that are important for airside cargo transportation:

- Pick-up time: time interval when a truck can pick up cargo at the terminal or the aircraft to be transported over airside.
- Delivery time: time interval when a truck can deliver cargo at the terminal or aircraft stand.
- Security/handling: whether the cargo requires a special form of airside cargo transportation. For instance, for special cargo transportation due to dangerous or valuable goods.
- Size: airside cargo transportation in ULDs or any other form.
- Weight

Airside cargo transportation depends on other activities within the air cargo supply chain and the airport's operation. This introduces uncertainty into the airside cargo transportation process. For instance, the reliability of the Kaagbaantunnel also results in uncertain tunnel availability. Uncertainty is also introduced by the unpredictability of the demand for air cargo demand due to short time intervals between bookings and transportation and the common situation of (partial) cargo no-shows [11]. Moreover, uncertainty arises from delayed flight or landside transport, influencing the pick-up and delivery time. Finally, the aircraft gate assignment determines the demand location.

In this research, the cargo transportation system refers to all things working together to provide airside cargo transportation as part of a complex whole. The system can be divided into smaller subsystems, which are also systems on themselves. The cargo transportation system is divided into the cargo transportation process and the service road network. In a later stage, these subsystems are further analyzed.

For clarity, the current and new state of the cargo transportation system is defined. The current cargo transportation system refers to the current situation at Schiphol in 2024 and consists of:

- Current service road network: including the current KLM Cargo Terminal (CCT) (Vrachtgebouw 1, 2, and 3) located at Schiphol Centre.
- Current cargo transportation process: in which belly cargo is transported between the CCT and passenger aircraft.

The new cargo transportation system refers to the Schiphol situation that arises after the KLM Cargo's relocation to CargoCity. Definitions within this new system are referred to as:

- New service road network: including the New KLM Cargo Terminal (NCT), located at Schiphol Southeast. After this relocation, all of Schiphol's cargo terminals are located at Schiphol Southeast, also named CargoCity.
- New cargo transportation process: in which belly cargo is transported between the NCT and passenger aircraft.

The research evaluates the effect of various strategies on the system's performance. These strategies comprise any change in part of the new system.

## 1.2. Research Objective

In Schiphol's cargo transportation system, the cargo transportation process uses the service road network to pick up and deliver commodities between cargo terminals and aircraft stands. The entire system can be formulated as a Pick-up and Delivery Problem (PDP) in which multiple characteristics differentiate commodities, including the pick-up and delivery time. As mentioned before, Schiphol's service roads are crowded, influencing travel speed. In addition, the utilization of cargo vehicles is inefficient, resulting in a loss of effective service road capacity. Besides, several factors introduce uncertainty in the system, such as tunnel availability, cargo demand, cargo arrival and departure time, and aircraft stand allocation. Thus, the current cargo transportation system already has its own complications.

In addition, relocating cargo terminals to CargoCity will change Schiphol's airside cargo transportation system. In particular, the Kaagbaantunnel's capacity and reliability are important new characteristics of the service road network. This leads to additional complications in the belly cargo transportation system between CargoCity and Schiphol Centre. Consequently, the new belly cargo transportation system might not perform optimally due to the current and new complications. Hence, changes to the system might improve the performance of the belly cargo transportation system. Changes to the system are hereafter referred to as strategies.

This study aims to identify a belly cargo transportation strategy that improves the new system between Schiphol Centre and CargoCity. The research objective is:

> *Determine an optimal cargo transportation strategy for belly cargo between CargoCity and passenger aircraft stands at Schiphol Centre after KLM Cargo's relocation by using a Pick-up and Delivery Problem formulation.*

## 1.3. Research Questions

To achieve the objective, the main research question addressed during the thesis is:

> *What cargo transportation strategy can be used to optimize the system used to transport belly cargo between CargoCity and passenger aircraft stands at Schiphol Centre after KLM Cargo's relocation to CargoCity?*

The main research question is divided into five subquestions, defined as follows:

1. What is the current state of the belly cargo transportation system, and what will change in the system when KLM cargo relocates to the NCT?
2. What are critical points within the current and new belly cargo transportation system that limit the system's performance?
3. What are the belly cargo transportation system's requirements, and how can the system be modeled as an Mixed-Integer Linear Programming (MILP) model while satisfying these requirements?
4. Which belly cargo transportation strategies can be implemented in the belly cargo transportation system, and how can these be modeled?
5. How do different belly cargo transportation strategies affect the performance of the belly cargo transportation system?

## 1.4. Scope

The scope of this research is confined to the airside cargo transportation process between the cargo terminal and the aircraft stands. This process scope is visualized in Figure 1.2.

After the relocation of KLM Cargo to CargoCity, all full freight aircraft are assumed to be assigned to freighter aircraft stands at Schiphol Southeast. This implies that cargo transportation between cargo terminals and freighter aircraft stands is short and does not use the Kaagbaantunnel. Therefore, only the belly cargo transportation is included in the problem.

Besides, the research concerns the route planning stage of airside cargo transportation. Route execution is not part of the research. Hence, flows are studied, while collision avoidance is not included in the research.


Figure 1.2: Visualization of the airside cargo transportation process with scope boundaries specified in blue

## 1.5. Proposal structure

The remainder of this proposal starts with a literature review of PDPs with numerous variations related to the proposal's problem in Chapter 2. In Chapter 3, the proposed research framework is discussed in detail, including the research activities and methods. Accordingly, Chapter 4 provides the thesis planning containing all these activities.

# 2

# Literature review

The airside cargo transportation system can be described as a PDP. PDP is a widely studied problem, which will be discussed in Section 2.1. After which, the incorporation of some significant network characteristics into a routing problem is discussed in Section 2.2. Section 2.3 reviews relevant studies within the airport cargo transportation industry. Finally, the proposed literature gap to be filled by this thesis is described in Subsection 2.4

## 2.1. Pick-up and Delivery Problem

The PDP originates from the Travelling Salesman Problem (TSP). The TSP describes the problem of finding the route with the least costs for a vehicle to visit every customer in a network exactly once and returning to the first customer [16]. The network can be modeled as a graph with nodes and edges. Nodes represent customers, and edges represent the distance between two customers. A generalization of the TSP is the Vehicle Routing Problem (VRP). The VRP describes the problem of finding a set of least-cost routes for a vehicle to visit every customer exactly once while starting and ending each route from a depot [10]. Compared with the TSP, multiple routes can be constructed and executed by one or multiple vehicles. A generalization of the VRP is the Pick-up and Delivery Problem (PDP) (or the Vehicle Routing Problem with Pick-up and Delivery (VRPPD)), which describes the problem of assigning a set of least-cost routes to a vehicle such that commodities are picked up and delivered between locations in a network. Lokin [21] first described the PDP variation of the VRP. Compared to the VRP, additional constraints regarding precedence relations are included in the problem formulation to ensure that a commodity is picked up before delivery. The PDP is a widely studied problem as different problem characteristics result in numerous variations. Psarafatis et al. [26] and Berbeglia et al. [4] define classification schemes to describe various PDP characteristics. Even though characteristics are distinct, some characteristics are interdependent.

The context of this proposal's problem already defines fixed characteristics that should included in the PDP formulation, while other PDP characteristics remain undefined during this proposal stage. First, the fixed and unfixed PDP characteristics of the problem formulated in this proposal are defined in Subsection 2.1.1. Then, literature with (almost) similar fixed characteristics and various combination of the unfixed characteristics are reviewed. Subsection 2.1.2 and Subsection 2.1.3 review PDP that are both deterministic, while the PDPs in the first Subsection are static and in the latter the PDPs are dynamic. Subsection 2.1.4 describes static and stochastic PDPs. Finally, dynamic and stochastic PDPs are reviewed in Subsection 2.1.5

### 2.1.1. Characteristics of the Pick-up and Delivery Problem

The structure of the PDP at hand is one-to-one (1-1). This means that a commodity has a specific pick-up and delivery node, sometimes called paired pick-ups and deliveries. Multiple vehicles are considered in the problem. However, whether the number of vehicles is limited or unlimited depends on other characteristics. At customer nodes, commodities are picked up and/or delivered, which might be performed either separately or combined. The commodity pick-up and delivery times are important for the context of the proposal's problem. Accordingly, time constraints in the form of the earliest pick-up and delivery time windows are part of the PDPs' formulation. A distinction is made between hard and soft time windows. Hard time window constraints cannot be violated, while soft time window constraints can be violated in return for a penalty in the objective function. Whether time window constraints are hard or soft is not yet defined, as this decision also depends upon other PDP characteristics. Finally, the problem context specifies that vehicles have limited capacities and that pick-up and delivery requests may not be rejected.

The type of time constraint, limited or unlimited vehicles, and customer rejection are interdependent PDP characteristics, as some combinations can lead to infeasible problems. In the proposal's problem context, only customer rejection is fixed. The other two characteristics (multiple vehicles and some type of time constraints) are partially defined. Their exact formulation is defined in a later stage of the research.

Unfixed characteristics are the type of problem, objective function, and solution method. PDPs can be classified into four types of problems: Static and Deterministic (SD), Static and Stochastic (SS), Dynamic and Deterministic

(DD), and Dynamic and Stochastic (DS). A PDP is SD unless otherwise specified. Static in the PDP context means all inputs are available and fixed before the routes between requests are determined. Deterministic in PDPs means all inputs are known with certainty. Dynamic refers to the fact that inputs are received and/or updated simultaneously with the route determination and execution. The following dynamic elements can be included in PDPs according to literature ([26], [6]): requests (including new requests, cancellations, changes in locations, and/or demands), vehicle availability, travel times, and service times. The first three elements could fit the problem definition. As mentioned before, the demand in the air cargo industry is highly unpredictable due to the short time intervals between booking and transportation and cargo (partial) no-shows [11]. Besides, the vehicle availability for airside cargo transportation depends on the materials and drivers available. The travel times rely on the service road network's real-time traffic and road conditions. The loading and unloading of dollies by the truck would result in service times; however, variations in service times are outside the scope of this research. Stochastic, in terms of the PDP, refers to inputs with probabilities or probability distributions. Psaraftis et al. [26] and Oyola et al. [25] distinguish the following stochastic elements: request (location and demand size), travel time, and service time. Again, variation in service time is outside the scope of this research, but the other two stochastic elements could fit the problem's context. It is argued that solving the PDP without considering real-life conditions or uncertainties during the planning stage results in poor results in the operational stage [30].

The problem's objective function is not yet defined at this stage. Common minimization objective functions in PDPs are route cost, route distance, travel time, total lateness, number of vehicles, service cost, customer dissatisfaction, and makepan. Common maximization objectives in the PDP are quality of service and profit. Multiple objectives are also frequently used in PDPs.

Finally, the solution method is a very broad class. PDP can be solved using exact, heuristic, meta-heuristic, and learning-based methods. The solution method is usually selected based on considering computational time and acceptable deviation from the optimal solution.

Exact methods provide optimal solutions, such as branch-and-bound, branch-and-cut, and branch-and-price algorithms. These algorithms only provide optimal solutions in the current state of the problem and thus do not guarantee optimality in dynamic PDPs, where new information arrives throughout the solution process [6]. Besides, the PDP problem is computationally complex and belongs to the class of NP-hard problems. Subsequently, solving the problem to optimality within a reasonable computational time requires small problem instances. According to Cai et al. [6], there is little hope of substantially improving exact methods to solve larger instances. However, exact methods are sometimes combined with other solution methods to solve the problem.

Heuristics usually obtain good-quality results in short computational times by using simple rules. A frequently used heuristic in PDPs is the insertion heuristic, in which a set of small initial routes are extended by inserting customers into the route [6]. Local search heuristics are also used to solve the PDP [4]. This heuristic starts with an initial feasible solution, which is a set of feasible routes. The neighborhood of the solution is explored to find slightly different solutions. Once an improved solution has been found, that solution is adopted. Accordingly, the process is repeated iteratively until no improved solution can be found.

Meta-heuristics are problem-independent algorithms that use strategies to develop heuristics for an optimization problem. The main meta-heuristics used to solve PDPs are Variable Neighborhood Search (VNS), Tabu Search (TS), Evolutionary Algorithm (EA), and Swarm Intelligence (SI). VNS systematically changes the search space of local search to avoid getting trapped in local optima and search the solution's neighborhood more extensively. TS searches the solution space by iteratively moving from a current solution to the best neighboring solution, even when this leads to deteriorating objective value. Moving from a current solution to the previous solution is prohibited for a certain number of iterations. EA are techniques based on biological concepts, including the Genetic Algorithm (GA). GA is inspired by the biological natural selection process. It starts with a set of feasible solutions, of which the best solutions are iteratively changed using mutation and cross-over procedures. Finally, SI is inspired by the behavior of natural systems. Two commonly used SI algorithms are Ant Colony Optimization and Particle Swarm Optimization. Both are based on a population of agents interacting with an environment to achieve a collective goal.

The final class of solution methods is learning-based methods, in which models learn from training sets to determine an optimization approach for a problem. However, as this solution method requires training sets, it is not deemed applicable to this problem context. Therefore, only exact methods, heuristics, and metaheuristics are considered in further literature review.

In summary, the proposal's problem is a 1-1 PDP with multiple vehicles, time constraints, limited vehicle capacity, and no customer rejection. The criteria that are still open for definition are a type of time constraint, limited or unlimited number of vehicles, type of problem, objective function, and solution method. Unless indicated otherwise, all papers presenting a PDP in the literature review have similar characteristics as the fixed characteristics of the proposal's problem. The purpose of the coming subsections is to present an overview of relevant papers with different unfixed characteristic combinations.

For a full review of all possible characteristic combinations, refer to one of the following surveys: [4] for a survey on static PDPs, to [6] for a review of dynamic PDPs, [25] for a review on stochastic PDPs, and to [26] for a survey of dynamic and/or stochastic PDPs.

### 2.1.2. Static and Deterministic Pick-up and Delivery Problem

Three SD PDPs are reviewed and an overview is provided in Table 2.1. Dumas et al. [12] present a PDP in which the time windows are hard, and the number of vehicles is unlimited. The latter is minimized in the objective, together with the total travel cost. The paper formulates the PDP as a Set Partitioning Problem (SPP). To solve the PDP with an SPP, a set of all possible feasible routes is generated. The goal of the SPP is to select the subset of routes that satisfies the constraints while optimizing the objective. The paper proposes an exact algorithm to solve the problem using column generation. The paper illustrates that time windows and the number of requests significantly influence the algorithm's computational time. The problems evaluated in this problem range between 19 and 55 requests. Mitrovi-Mini and Laporte [23] solve a PDP using an insertion heuristic. This research studies a PDP with transhipments and shows that the use of transhipments reduces total travel distance, especially in large problem instances. Nanry and Barnes [24] propose a TS for the PDP. Results show that this metaheuristic's computational time is consistently faster than that of exact methods while optimal or near-optimal solutions are obtained.

Table 2.1: Reviewed papers of SD PDPs with identical characteristics to the proposal's problem

| **Ref** | **Type** | **Time constraint** | **Amount of vehicles** | **Dynamic element** | **Stochastic element** | **Solution method** | **Deviation** | **Addition** |
|---|---|---|---|---|---|---|---|---|
| [12] | SD | Hard | Inf. | | | Exact + CG | | SPP |
| [23] | SD | Hard | Inf. | | | Insertion | | Transhipments |
| [24] | SD | Soft | Limited | | | TS | | |

### 2.1.3. Dynamic and Deterministic Pick-up and Delivery Problem

Six DD PDPs are reviewed with varying stochastic elements. An overview of these papers is provided in Table 2.2. Fabri and Recht[15], Cheung et al. [8], and Li et al. [20] all present a dynamic PDP with similar characteristics to this proposal's problem, except that they all allow for customer rejection. This is required to avoid infeasible problem formulations, as the time windows are hard and the number of vehicles is limited. Fabri and Recht [15] include dynamically arriving requests into the problem. It proposes a two-stage solution algorithm that first assigns requests to vehicles using a local search heuristic, after which the vehicles are optimally routed. Whenever a new request arrives, it is either accepted or rejected based on whether a feasible solution can be found for a vehicle while incorporating the new request. Cheung et al. [8] include both dynamically arriving requests and dynamic travel times. Dynamic travel times are obtained by translating real-time GPS data (such as vehicle location and distribution over the network) into travel time. The problem is solved by initially solving a static problem using a GA. A re-optimization is performed every time a request or travel time update arrives. A new request is either served by a new vehicle,ăif not all vehicles are occupied. Otherwise, the request is inserted into an existing route using an insertion heuristic, after which a refinement procedure is applied to improve the solution. A request is rejected if there is no feasible way to include it in the solution. The refinement procedure is also applied after travel time updates because this influences the total travel time objective. The dynamic element in Li et al. [20] is vehicle availability, in which the problem formulation allows for service disruptions due to vehicle breakdowns. Accordingly, vehicles need to be rerouted to perform unfinished requests by broken-down vehicles. The solution method is an insertion heuristic combined with Lagrangian relaxation.

Beaudry et al. [3] consider a Dial-a-Ride Problem (DARP), which is a special form of the PDP in which persons are transported instead of goods. The paper describes the problem of patient transportation in hospitals where new requests arrive dynamically. At initialization, empty routes are scheduled. Beaudry et al. [3] use a two-stage solution approach that is iteratively used whenever a new request arrives. First, a new request is inserted into an existing route, after which the current solution is optimized using an improved TS. Taniguchi and Shimamoto [29] present a similar PDP with dynamic travel time; apart from that, it is not a 1-1 problem. Instead, the problem is formulated as a one-to-many-to-one (1-M-1) problem that considers the transportation of one commodity type between a depot and customers. The travel times are determined and updated using a dynamic traffic simulation. This simulation consists of two components: flow simulation and route choice simulation. The study adopts a GA to calculate a solution, which is recalculated every time the travel time is updated. Results of the study indicate that including real-time dynamic travel times in the model reduces total costs compared to forecasting travel times. Haghani and Jung [18] describe a PDP with time-dependent travel times and dynamic requests. The PDP has a one-to-many-to-one structure instead of a 1-1 structure as the proposal's problem. In this problem, one type of commodity is considered that is transported between customers and a depot. The problem's time period is divided into discrete time intervals. Accordingly, a travel time is defined for every network connection at all intervals. Every time interval, the travel times are updated, new requests are incorporated into the existing routes, and the routes are revised. If this leads to infeasibility, new vehicles are included in the problem. This study shows that the dynamic version of the PDP becomes superior to the static PDP when uncertainty in travel time increases.

Table 2.2: Reviewed papers of DD PDPs with identical characteristics to the proposal's problem

| Ref | Type | Time constraint | Amount of vehicles | Dynamic element | Stochastic element | Solution method | Deviation | Addition |
|---|---|---|---|---|---|---|---|---|
| [15] | DD | Hard | Limited | Requests | | Exact + LS | CR | |
| [8] | DD | Hard | Limited | Requests + TT | | GA | CR | GPS data |
| [20] | DD | Hard | Limited | Vehicle avail. | | Insertion + LR | CR | Vehicle failure |
| [3] | DD | Soft | Limited | Requests | | Insertion + TS | DARP | |
| [29] | DD | Soft | Limited | TT | | GA | | |
| [18] | DD | Soft | Limited | Requests | | GA | 1-M-1 | Time dep. TT |

### 2.1.4. Static and Stochastic Pick-up and Delivery Problem

Typically, stochastic formulations of the PDP contain one or two stochastic elements due to the difficulty of solving problems with many stochastic elements [25]. The reviewed SS PDPs are summarized in Table 2.3.

Christiansen and Lysgaard [9] present a PDP with stochastic demand size, meaning that only a probability distribution of customers' demand size is known when the routes are determined. The structure of the PDP is many-to-many (M-M) instead of 1-1, meaning that a customer's pick-up demand can be used to satisfy the demand of any delivery customer. The paper formulated the PDP as an SPP, which is solved using a column generation algorithm.

Tas et al. [30] and Tas et al.[31] both present an M-M PDP including stochastic travel times. The travel times used have a known probability distribution, and the actual travel times become available after finding the solution. Consequently, earliness and lateness at a customer are penalized in the objective function. Tas et al. [30] first construct a feasible solution using an insertion heuristic while taking into account the stochastic travel time variations. The feasible solution is then improved by using a TS. In [31], the problem is formulated as an SPP, and an exact solution is found by combining column generation with a branch-and-price algorithm.

Table 2.3: Reviewed papers of SS PDPs with identical characteristics to the proposal's problem

| Ref | Type | Time constraint | Amount of vehicles | Dynamic element | Stochastic element | Solution method | Deviation | Addition |
|---|---|---|---|---|---|---|---|---|
| [9] | SS | Hard | Limited | | Request | Exact + CG | M-M | SPP |
| [30] | SS | Soft | Limited | | TT | Exact + CG | M-M | |
| [31] | SS | Soft | Limited | | TT | Insertion + TS | M-M | SPP |

### 2.1.5. Dynamic and Stochastic Pick-up and Delivery Problems

Three papers that combine dynamic and stochastic elements are reviewed. An overview is provided in Table 2.4. Schilde et al. [28] consider a DARP including dynamic requests, time-dependent travel speed, and stochastic travel speeds. Some requests are static, while others become known after the start time of the problem. Time-dependent travel speeds are determined based on historical data before the problem starts. Actual travel speeds, including stochastic influences, are revealed once a vehicle departs. Routes cannot be changed after the vehicle departs the depot, while the actual travel speeds influence the objective value. Besides, the influence of traffic accidents on travel speed is included using the probability of accidents during hours of the day based on historical accidents. The model is solved using a two-stage approach. First, an initial solution is generated in which requests are sequenced into routes, after which the routes are improved using a dynamic or dynamic stochastic variation on the VNS. Second, the routes are scheduled based on time constraints while considering time-dependent travel times. Introducing time-dependent and stochastic travel speeds into the problem significantly reduces time window violations in real-life situations, as changing traffic conditions are considered.

Yang et al. [37] propose a similar PDP problem as described in this proposal, except that it allows customer rejection, extended by dynamic requests. The paper evaluates several optimization strategies, including a policy considering stochastic requests with a known probability distribution. Results indicate that the strategy, including stochastic requests, performed best.

Xiang et al. [36] introduce a dynamic and stochastic PDP that satisfies the fixed criteria, except that it allows customer rejection. The dynamic element is the requests that arrive throughout the problem, and the travel times are stochastic.

Table 2.4: Reviewed papers of DS PDPs with identical characteristics to the proposal's problem

| **Ref** | **Type** | **Time constraint** | **Amount of vehicles** | **Dynamic element** | **Stochastic element** | **Solution method** | **Deviation** | **Addition** |
|---|---|---|---|---|---|---|---|---|
| [28] | DS | Soft | Inf. | Request | Requests + TT | Multiple heuristics | DARP | Time dep. TT |
| [37] | DS | Hard | Limited | Requests | Location | Insertion + LS | CR | |
| [36] | DS | Hard | Limited | Requests | TT | Insertion + LS | DARP, CR | |

## 2.2. Network characterisitics

Two main aspects of the airside cargo transportation system at Schiphol are two characteristics of Schiphol's service road network: the service roads' capacity, including that of the Kaagbaantunnel, and the Kaagbaantunnel's reliability. This section reviews related papers on PDP-related problems incorporating flow-dependency and tunnel availability in Subsection 2.2.1 and Subsection 2.2.2.

### 2.2.1. PDP and flow-dependent travel times

Some references to PDPs with stochastic and dynamic travel times were already presented in the previous section. Cheung et al. [8] use GPS data to update traffic conditions dynamically, while Taniguchi and Shimamoto [29] use a traffic simulation model based on real-time traffic distributions for this purpose. The first approach can only be used during the operational use of the model, as actual GPS data is required. The latter requires a separate simulation model. Besides, Haghani and Jung [18] and Schilde et al. [28] include time-dependent travel times and speeds, respectively. An average travel time or speed is determined for each time period. Tas et al. [30] and Tas et al. [31] use stochastic travel times, in which real travel times only become available after the routes are determined. These models aim to construct routes considering possible travel time variations. These approaches require knowledge about traffic distribution before solving the problem. They do not consider the effect of the vehicles scheduled by the problem on the resulting traffic flow. Subsequently, the effects of traffic flows exceeding the road's capacity are not included. Although it is known that traffic flow, capacity, and travel speed are strongly related [35].

Even though traffic flow and travel speed are highly dependent upon each other, not one PDP with flow-dependent travel speed (or travel time) has been found in the literature. Besides, only limited work considering flow dependency within PDP-related problems has been found. Two papers are discussed in which the effect of the scheduled traffic is taken into account in determining the travel times.

Van Woensel et al. [35] describe a VRP with dynamic travel times based on the queueing theory. It considers an unlimited number of vehicles with limited capacity, no time windows, and no customer rejection. Moreover, it compares the queueing theory approach for dynamic travel times with two descriptive approaches. The first descriptive approach is time-independent travel times in which an average speed for the entire time period is determined. The second descriptive approach is time-dependent, in which the time period is divided into three time steps, and an average speed for each time step is determined. These approaches model the outcome of the speed-flow-density diagrams, which describe the traffic flow theory. In contrast, the queueing theory approach models the underlying process that results in the speed-flow-density diagram, allowing a more analytical approach. The presented model by Van Woensel et al. [35] divides roads into road segments of a minimum vehicle length. Each road segment is considered as a service station. The time a vehicle travels through the service station is called the service time. The paper uses a state-dependent GI/G/m queueing model in which the service time is a function of the traffic flow. The service time of each service station is determined based on the length of the service station and speed. The speed can be determined by correcting the free flow speed with a congestion factor. The free flow speed is the speed without any waiting time (due to congestion). The congestion factor depends on several factors based on traffic conditions and network characteristics. In the flow-dependent model, the speed for every service station is updated every 10 minutes based on traffic conditions. The model uses a TS solution method. Results show that the queueing approach outperforms the other approaches significantly in terms of minimizing travel costs, although computational times increased.

Hou et al. [19] consider a ride-matching problem with associated vehicle routing. It is closely related to the DARP model, but the drivers themself also have an origin and destination in which the ride-matching should be inserted. The model has hard time windows, limited vehicle capacity, a limited number of vehicles, and customer rejection is allowed. The paper presents a flow-dependent model in which the delays at nodes depend on the traffic flows on closely located arcs. The paper suggests that congestion at one point of the network influences geographically close areas. Therefore, it defines the network into several areas that are geographically close. Accordingly, delays are modeled as service times at nodes using a delay function. The delay function is defined for each area using an M/M/1 queueing model based on service times without delays and the flow on arcs within the area. This delay function is incorporated into the constraint that defines node arrival times. The model uses a LNS heuristic. The objective function of the model is to minimize the total travel time. As expected, the objective function was significantly increased compared to an instance of the problem that does not consider any congestion. In addition, the computational time increased increased.

| Ref | Type | Time constraint | Amount of vehicles | Dynamic element | Stochastic element | Solution method | Deviation | Addition |
|---|---|---|---|---|---|---|---|---|
| [35] | DD | Non | Limited | TT | | TS | VRP | Queueing theory |
| [19] | DD | Hard | Limited | TT | | LNS | CR, DARP+ | |

### 2.2.2. PDP and tunnel reliability
Despite the fact that network uncertainty can be caused by various reasons (road blockades, traffic accidents, road construction), no PDP or PDP-related studies regarding dynamically changing networks have been found during this literature review. However, uncertain networks are included in humanitarian logistic designs, in which emergency support should be distributed as quickly as possible after a natural disaster to minimize human suffering and deaths. These models consider uncertain road availability due to the chance of a natural disaster closing a road. For instance, Mete and Zabinsky [22] and Tofighi et al. [32] both consider a two-stage approach. In the first stage, humanitarian logistics are planned without knowing the effects of the natural disaster. During the second stage, road unavailability due to natural disasters becomes accessible. The planned humanitarian logistics are adjusted accordingly. In both papers, road unavailability is implicitly modeled as very long (almost infinite) travel times.

## 2.3. Airport Cargo transportation
This final section presents transportation-related studies on airport cargo transportation, which can be divided into landside and airside transportation. In landside transportation, the cargo is transported by trucks between the freight forwarder and the cargo handler. Although landside cargo transportation is outside this research's scope, many similarities can be found with airside cargo transport. Hence, studies on landside transport are reviewed in Subsection 2.3.1. Airside cargo transportation involves all activities between the cargo handler's landside and the aircraft. The activities within the cargo terminal are outside the scope of this research. Hence, only the transportation between the cargo handler's airside and the aircraft is considered in the airside cargo transportation. Papers on airside transportation are discussed in Subsection 2.3.2. PDP papers on both landside and airside transportation are summarized in Table 2.5.

### 2.3.1. Landside cargo transportation
Many articles study landside cargo transportation at airports. Azadian et al. [2] present a PDP concerning landside cargo transportation from the freight forwarder's perspective in a multi-airport region. The goal of the problem is to optimize the pickup and delivery of cargo between the freight forwarder's depot and one of the airports, taking into account airports' flight itineraries. The PDP is DD with one commodity type and considers soft time windows, limited vehicles, and no customer rejection. The included dynamic element is time-dependent delivery costs. The model is solved using a Successive Subproblem Solving (SSS) method. Bombelli and Fazi [5] demonstrate the benefits of collaboration among freight forwarders in landside cargo transportation under truck docking space constraints using a hybrid version of the PDP and a Machine Scheduling Problem (MSP). The PDP concerns truck routing, while the latter schedules the sequence of the trucks at the ground handlers' docks. The PDP is formulated as an SD with one commodity type that does not allow customer rejection, contains hard time windows, and has a limited number of trucks. The model is solved using CPLEX, but a variation on the LNS metaheuristic has been developed to improve computational times.

Ankersmit et al. [1] and Romero-Silva and Mota [27] consider the potential of horizontal collaboration by freight forwarders in landside cargo transportation between cargo handlers and customers using a simulation model of Schiphol. Collaborating freight forwarders share their truck capacity to transport consolidated cargo shipments Ankersmit et al. [1] consider one ground handler and multiple freight forwarders, which are all collaborating. This study's main finding is that collaboration among all freight forwarders can significantly improve the performance of landside cargo transportation while reducing costs. Romero-Silva and Mota [27] consider all five ground handlers at Schiphol Airport and include that only part of the freight forwarders collaborate. This study shows that horizontal collaboration is not always beneficial when not all freight forwarders are included in the collaboration. In some cases, the collaboration of some freight forwarders only benefits the non-collaborating freight forwarders.

### 2.3.2. Airside cargo transportation
To my best knowledge, the only airside cargo transportation-related research studies the redesign of KLM Cargo's cargo handling procedure for outbound cargo to comply with the Clean VOP strategy of Schiphol Airport [34]. The study evaluates different cargo handling strategies using a Discrete-Event Simulation. The strategies are push systems, pull systems, and variations on such systems. The main difference between this study and the research proposed in this proposal is that it is a simulation study that focuses on the interaction of the vehicles within the environment, while the proposed research aims to study the flow of the network. Besides, van Rugge [34] exclusively concerns outbound cargo and no dynamic elements are included, only stochastic aircraft arrival times.

Other studies that consider airside transportation consider other ground-handling activities other than cargo transportation. For instance, Guo et al. [17] propose an improved GA to be applied to solve airside baggage transport PDP. The PDP considers the pick-up and delivery of baggage between a depot and an aircraft. The PDP is SD, contains hard time windows, unlimited vehicles with limited capacity, and does not allow customer rejection. Zhu et al. [38] study a VRP of two types of ground handling services (refuellers and shuttle buses) considering flight arrival time uncertainty. The VRP is SS and contains soft time windows, a limited number of vehicles, and does not allow customer rejection. The model is solved using CPLEX. The aim of including this uncertainty is to increase resource utilization by minimizing service costs and time losses. The study demonstrates that including flight time uncertainty results in significant service improvement.

Moreover, recent studies on airside transportation focus on autonomous airside transportation. Chen et al. [7] and van der Zwan [33] consider fully autonomous ground handling. Whereas Duzijn [13] focuses on towing operations only. Instead of using a linear programming approach, these studies use agent-based modeling to allocate tasks among agents and route collision-free paths. The latter is not an objective in this study.

Table 2.5: Reviewed papers of PDPs (or related models) within airport cargo transportation

| Ref | Type | Time constraint | Amount of vehicles | Dynamic element | Stochastic element | Solution method | Deviation | Addition |
|---|---|---|---|---|---|---|---|---|
| [2] | DD | Soft | Limited | Delivery cost | | SSS | | |
| [5] | SD | Hard | Limited | | | Exact + LNS | PDP + MSP | Collaboration |
| [17] | SD | Hard | Inf. | | | GA | | |
| [38] | SS | Soft | Limited | | Task arrival | Exact | VRP | |

## 2.4. Literature gap

In summary, the PDP is a widely studied problem with numerous characteristic combinations applied to many logistical problems. However, the PDP has not yet been applied to airside cargo transportation, which will be the focus of the proposed thesis. Airside cargo transportation contributes considerably to the overall traffic movements on the service roads. Therefore, the impact of airside cargo transportation on traffic flow needs to be considered. Traffic flow is related to travel speed and, accordingly, to travel time. Hence, including flow-dependent travel times in the PDP is fundamental. The only two papers found using flow-dependent travel times incorporate queueing theory into a VRP and a DARP. To my best knowledge, no literature on PDPs with flow-dependent travel times is available. This is the knowledge gap that the proposed thesis aims to fill. Finally, the thesis also aims to incorporate stochastic road availability into a PDP, as tunnel closure is a main characteristic of the studied service road network at Schiphol. The incorporation of road availability in a PDP has also not been encountered during this literature study.

# 3
# Methodologies

A research framework is used to structure and systematically perform the thesis research. The proposed research framework is an adapted version of the Engineering Design Process by [14]. According to Dym and Brown, the Engineering Design Process is "the systematic, intelligent generation and evaluation of specifications for artifacts whose form and function achieve stated objectives and satisfy specified constraints" [14]. In terms of this research, a new belly cargo transportation strategy is designed and evaluated. The strategy must perform a certain function while adhering to the requirements of the air cargo transportation system

The research framework comprises five phases: research proposal problem definition, conceptual design, strategy design, and the concluding phase. This research framework is presented in Figure 3.1. All phases, including their steps and methods, are described in detail below.

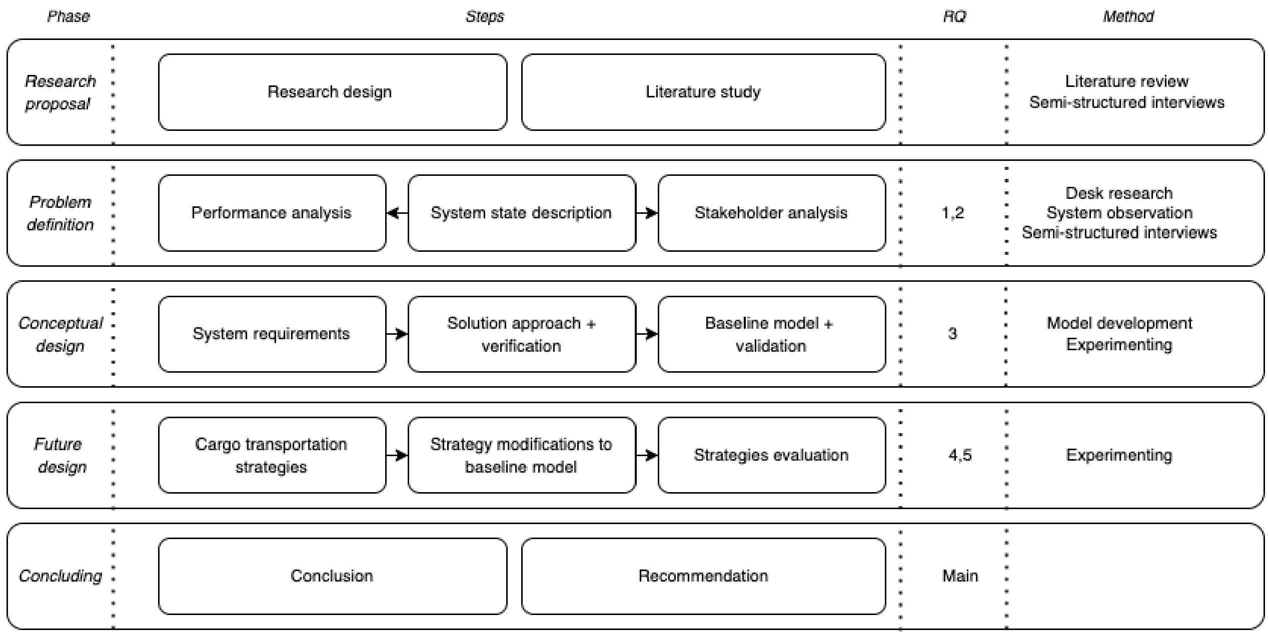



Figure 3.1: Research framework including phases and corresponding steps and methods

The *research proposal* phase involves the development of this research proposal. It outlines the context of the problem, objective, research questions, scope, assumptions, literature review, research framework, and research planning.

The objective of the *problem definition* phase is to understand the current state system thoroughly and to analyze the problems and shortcomings within the system subsequently. Desk research and expert interviews will map the state of the current and new cargo transportation system. The desk research is used to get a general overview of the system. However, not all aspects of the system are documented, especially not airport-specific or cargo handler-specific details. Therefore, expert interviews are fundamental to thoroughly understanding the system at Schiphol for cargo handlers such as KLM Cargo. Every step of the cargo transportation process is systemically outlined using an activity diagram (and/or swimlane diagram). This provides a detailed overview of the activities within the process that influence and depend upon each other. Moreover, a network analysis is performed to study the characteristics of different parts of the network and their interdependencies. These characteristics include capacity, average speed, traffic flow (of non-cargo handling vehicles), reliability, rules, and regulations. In particular, the Kaagbaantunnel, its specifications, and the tunnelwet are examined extensively. KPIs are identified and used to quantify the current system's performance. In addition, expectations for the new system's KPIs are predicted. This performance information is then used to expose and analyze critical points within the process, such as process shortcomings, bottlenecks, complexities, and/or unused redundancies. Root causes for the critical points are analyzed. In a later phase, these critical points are used to determine future cargo transportation strategies. Moreover, a stakeholder analysis is performed to obtain stakeholders' perspectives on the process. Their interest and power within the system are determined, which is used to decide how to weigh their perspectives and thoughts on the system, obtained during the expert interviews. In contrast, optional targets and restrictions are not crucial to constitute a representative system image.

The purpose of the *conceptual design* phase is to develop a baseline model for the system. The model requirements are defined based on the retrieved system information in the previous phase. These requirements also define further PDP characteristics, such as objective function, dynamic and stochastic elements, type of time constraints, and limited or unlimited number of vehicles. Accordingly, the model requirements are used to define the model's solution approach. The solution approach provides insight into the method used to obtain the desired outputs from the inputs. It comprises intermediate steps to be taken, such as data generation/preprocessing, PDP formulation, solution method, model assumptions, and simplifications. A queueing model that complies with the system requirements is integrated into the PDP formulation. Additionally, the availability of the tunnel is incorporated into the solution approach. Then, the solution approach is verified to assess whether it complies with the system requirements. Subsequently, a computer model in Python is assembled based on the validated conceptual model. The computer model is validated using the KPIs for the current and new cargo transportation systems. Real KPI values are used for the current system, and the expected KPI values are used for the new system.

Different cargo transportation strategies are evaluated in the *future design* phase. To do so, first, the different cargo transportation strategies are determined based on the identified critical points within the cargo transportation system. Then, a variation on the baseline model is constructed for every cargo transportation strategy by changing the model inputs or some of the constraints. Accordingly, the performance of the cargo transportation system under the various cargo transportation strategies is evaluated. This evaluation is performed using either a scenario or strategy analysis, which results in a ranking of the various strategies.

Finally, the *concluding* phase provides the main findings, conclusions, and recommendations of this research. In this phase, the main research question is answered.

# 4

# Planning

This chapter provides the research planning in Figure 4.1 and Figure 4.2. The planning includes the phases of the methodology and the corresponding steps of each phase. Red stars indicate deliverables or reviews. The provisional dates for the deliverables and reviews, in chronological order, are:

- Friday, 25 October 2024: Mid-term deliverable
- Friday, 1 November 2024: Mid-term review
- Wednesday, 13 January 2025: Draft thesis deliverable
- Wednesday, 5 February 2025: Green light review
- Friday, 28 February 2025: Research portfolio deliverable
- Friday, 14 March 2025: Thesis defense

Six weeks of the holiday have been included in the planning. Two weeks (Holiday W1 and W6) are fixed, while the dates of the other four holiday weeks are tentative. These four weeks can also be used for unforeseen circumstances like illnesses or other thesis work interruptions.

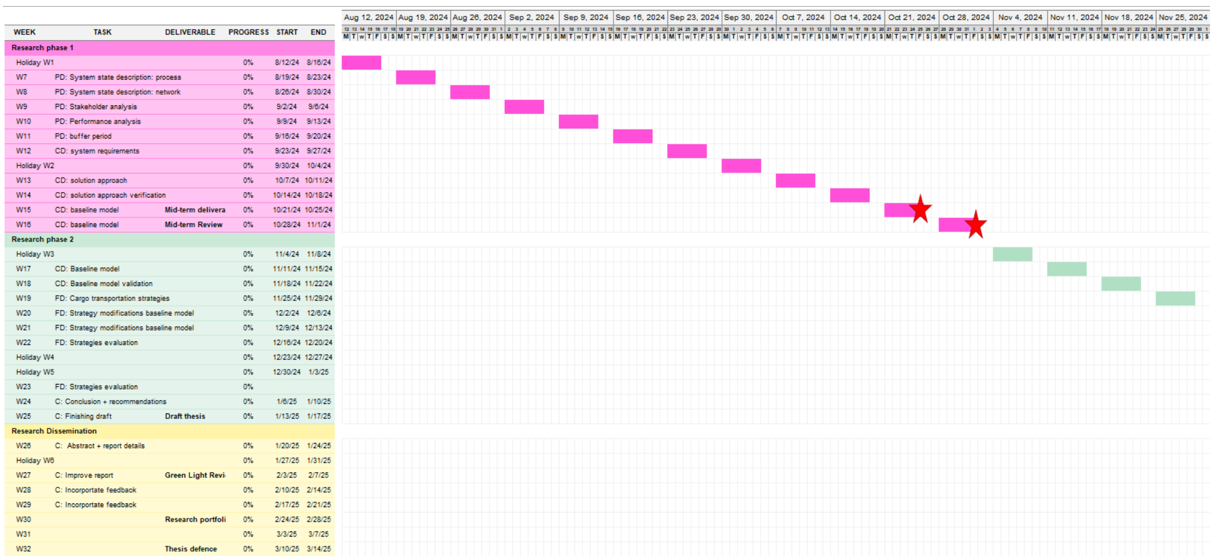
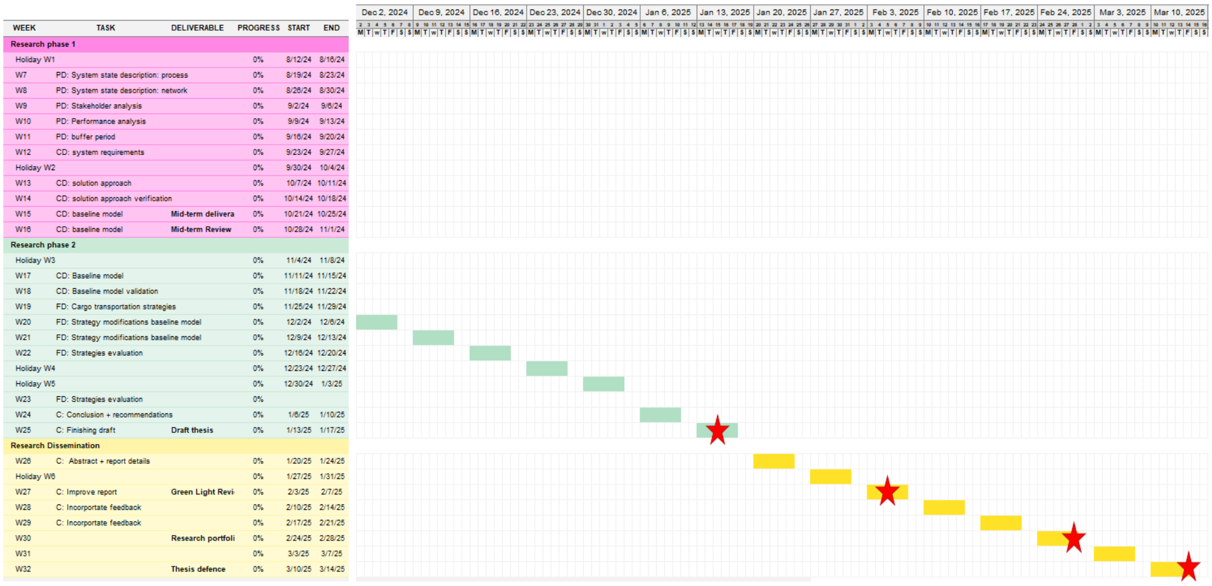



Figure 4.1: Thesis planning from thesis week 7 until week 19. PD = Problem Definition phase, CD = Conceptual Design phase, FD = Future Design phase, C = Concluding phase




| WEEK | TASK | DELIVERABLE | PROGRESS | START | END |
|---|---|---|---|---|---|
| **Research phase 1** | | | | | |
| Holiday W1 | | | 0% | 8/12/24 | 8/16/24 |
| W7 | PD: System state description: process | | 0% | 8/19/24 | 8/23/24 |
| W8 | PD: System state description: network | | 0% | 8/26/24 | 8/30/24 |
| W9 | PD: Stakeholder analysis | | 0% | 9/2/24 | 9/6/24 |
| W10 | PD: Performance analysis | | 0% | 9/9/24 | 9/13/24 |
| W11 | PD: buffer period | | 0% | 9/16/24 | 9/20/24 |
| W12 | CD: system requirements | | 0% | 9/23/24 | 9/27/24 |
| Holiday W2 | | | 0% | 9/30/24 | 10/4/24 |
| W13 | CD: solution approach | | 0% | 10/7/24 | 10/11/24 |
| W14 | CD: solution approach verification | | 0% | 10/14/24 | 10/18/24 |
| W15 | CD: baseline model | **Mid-term delivera** | 0% | 10/21/24 | 10/25/24 |
| W16 | CD: baseline model | **Mid-term Review** | 0% | 10/28/24 | 11/1/24 |
| **Research phase 2** | | | | | |
| Holiday W3 | | | 0% | 11/4/24 | 11/8/24 |
| W17 | CD: Baseline model | | 0% | 11/11/24 | 11/15/24 |
| W18 | CD: Baseline model validation | | 0% | 11/18/24 | 11/22/24 |
| W19 | FD: Cargo transportation strategies | | 0% | 11/25/24 | 11/29/24 |
| W20 | FD: Strategy modifications baseline model | | 0% | 12/2/24 | 12/6/24 |
| W21 | FD: Strategy modifications baseline model | | 0% | 12/9/24 | 12/13/24 |
| W22 | FD: Strategies evaluation | | 0% | 12/16/24 | 12/20/24 |
| Holiday W4 | | | 0% | 12/23/24 | 12/27/24 |
| Holiday W5 | | | 0% | 12/30/24 | 1/3/25 |
| W23 | FD: Strategies evaluation | | 0% | | |
| W24 | C: Conclusion + recommendations | | 0% | 1/6/25 | 1/10/25 |
| W25 | C: Finishing draft | **Draft thesis** | 0% | 1/13/25 | 1/17/25 |
| **Research Dissemination** | | | | | |
| W26 | C: Abstract + report details | | 0% | 1/20/25 | 1/24/25 |
| Holiday W6 | | | 0% | 1/27/25 | 1/31/25 |
| W27 | C: Improve report | **Green Light Revi** | 0% | 2/3/25 | 2/7/25 |
| W28 | C: Incorportate feedback | | 0% | 2/10/25 | 2/14/25 |
| W29 | C: Incorportate feedback | | 0% | 2/17/25 | 2/21/25 |
| W30 | | **Research portfoli** | 0% | 2/24/25 | 2/28/25 |
| W31 | | | 0% | 3/3/25 | 3/7/25 |
| W32 | | **Thesis defence** | 0% | 3/10/25 | 3/14/25 |

Figure 4.2: Thesis planning from thesis week 19 until week 32. PD = Problem Definition phase, CD = Conceptual Design phase, FD = Future Design phase, C = Concluding phase

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