The impact of implementing electric Ground Support Equipment (eGSE) on the capacity and demand of GSE fleets at airports

Koen Timmermans[a,*], Paul Roling[b], Remco Troquete[c], Gideon Wiebenga[d], Bilge Atasoy[a]

[a] *Department of Maritime and Transport Technology, Delft University of Technology, Delft, The Netherlands*
[b] *Department of Air Transport & Operations, Delft University of Technology, Delft, The Netherlands*
[c] *Department of Airport Strategy & Planning, NACO, The Hague, The Netherlands*
[d] *Ground Services Department, KLM Royal Dutch Airlines, Schiphol, The Netherlands*

Abstract

Airports and airlines are examining and committing to the electrification of Ground Support Equipment (GSE). To be able to estimate the required quantity of eGSE, the charging requirements of eGSE, the change of airport electricity requirements, and the scheduling possibilities of eGSE charging for the existing turnaround procedures, a model was developed to simulate and optimize the GSE operations at airports. This was done by means of a Task Scheduling Problem (TSP), that is optimized using Mixed-Integer Linear Programming (MILP). A case study was performed on KLM's GSE fleet at Amsterdam Airport Schiphol. Based on this, it was concluded that there is no difference in the capacity that can be achieved for GSE types that can last an entire day on a single battery charge. However, another group of GSE types experiences battery depletion before the day concludes, requiring measures to maintain the capacity. The results indicate the model's suitability for strategic decision-making. Next to that, the model is effective on an operational level. The use of the model has the potential to make the use of resources in the operation more efficient.

Keywords: electric ground support equipment, airport operations, ground handling, multi-objective optimization, vehicle scheduling, fleet optimization

1. Introduction

In 2017, the aviation sector was the second most important source of Greenhouse Gas (GHG) emissions in the transport sector after road traffic (European Commission, 2021), and it seems that these environmental problems will continue, as the current traffic growth is outpacing fuel efficiency improvements and reductions of emissions from other sectors (European Union Aviation Safety Agency, 2022). To mitigate climate change and control temperature rise, the aviation sector needs to reduce GHG emissions, like CO_2, and the emission of air pollutants from fossil fuels. According to Kirca et al. (2020) aircraft operations are accountable for the majority of the aviation carbon emissions. Hence, there are a number of projects going on to achieve technological advancements to introduce low emission aircraft (Brelje and Martins, 2019). And while aircraft dominate the carbon emissions in the aviation sector, Ground Support Equipment (GSE) also has a share (Kirca et al., 2020). GSE supports the turnaround process of aircraft between the arrival and departure at an airport (National Academies of Sciences, Engineering, and Medicine, 2015). Besides their contribution to carbon emissions (National Academies of Sciences, Engineering, and Medicine, 2015), GSE is known to have a significant contribution to the NO_x pollution (Kirca et al., 2020). In 2012, GSE accounted for 13% of

*Corresponding author

Email addresses: K.Timmermans@student.tudelft.nl (Koen Timmermans), P.C.Roling@tudelft.nl (Paul Roling), Remco.Troquete@naco.rhdhv.com (Remco Troquete), Gideon.Wiebenga@klm.com (Gideon Wiebenga), B.Atasoy@tudelft.nl (Bilge Atasoy)

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NO_x at all airports in the US (Benosa et al., 2018). According to Alruwaili and Cipcigan (2022) and Kirca et al. (2020), one path to cut airport related GHG emissions is to use low or zero-emission GSE and provide infrastructure provision for supporting decarbonization solutions since much of the GSE is at present powered by diesel or petrol fuel. Yim et al. (2013) estimated that electrification of GSE could avert 28% of the early deaths, caused by airport emissions in the UK. Hence, to reduce both carbon and air pollutant emissions from GSE at airports, airports and airlines are examining and committing to the electrification of GSE (Kirca et al., 2020; Francfort et al., 2007).

A number of challenges arise as a fully electrified fleet of GSE is realized. The two main challenges pertain the significantly longer charging time compared to refueling conventional fossil-fueled vehicles and the increased burden on the electric grid (Gulan et al., 2019). Electric versions already exist for a number of, especially smaller GSE types, but these are still being developed for other larger vehicles (Timmermans, 2023). For the early stage decision making of different stakeholders, such as 1.) airport operators, 2.) ground service providers, and 3.) airline companies, it is therefore important to be able to estimate the required quantity of electric GSE (eGSE) types, the charging requirements of eGSE, the change of airport electricity requirements, and the scheduling possibilities of eGSE charging for the existing turnaround procedures. Therefore, the primary focus of the research is the development of a model that can be used to gain insight into the operational requirements for the implementation of an eGSE fleet at airports.

This paper is organized as follows: Section 2 reviews the relevant literature. The conceptual framework is explained in Section 3. After that, the problem formulation is provided in Section 4. In Section 5 several measures to improve the solvability are discussed. The model is applied in a case study for KLM Royal Dutch Airlines at Amsterdam Airport Schiphol (AAS) in Section 6. The results are discussed in Section 7. Finally, conclusions and future research lines are provided in Section 8.

2. Literature review

This section presents a review of the existing literature on operations research that is considered relevant for this research. Section 2.1 discusses different works on the optimization of operations. Next, Section 2.2 reviews different works on energy management, including topics like charging (scheduling), and charging infrastructure as well. Most of the works being reviewed focus on GSE. However, some works focusing on (commercial) Electric Vehicles (EV) are included as well. After that, the scope is widened in Section 2.3, which looks into other related problems in the aviation industry. Finally, a comparison of the different works is provided in Section 2.4.

2.1. Optimization of operations

Scheduling GSE for airport operations is often treated as a VRPTW (Vehicle Routing Problem with Time Windows). Ip et al. (2013) address this problem with a hybrid assignment approach for multiple non-identical vehicles. A similar approach is taken by Padrón et al. (2016), who break down the VRPTW into distinct problems for each vehicle type, using Constraint Programming (CP) to minimize waiting time and total turnaround completion time. Padrón and Guimarans (2019) improved this work to reduce computational times. For baggage tugs, Wang et al. (2021) formulates the problem as a Mixed-Integer Linear Programming (MILP) model. When focusing on aircraft turnaround tasks and staff routing, Gök et al. (2022) treats the problem as a Resource-Constrained Project Scheduling Problem (RCPSP) and uses CP for team routing decisions. Another VRP formulation is presented by Bao et al. (2023), who establish a mixed operation model for aircraft towing tractors with time windows. Van Oosterom et al. (2023) also focus on the dispatching of a fleet of electric aircraft towing tractors. They propose a two-phased MILP program. The first phase takes care of the routing of the towing tractors. In the second phase, the towing tractors are scheduled for aircraft towing tasks or battery recharging. In the context of military aircraft handling, Zhang et al. (2022) suggest using an RCPSP instead of a VRP. They focus on resource allocation for job scheduling, emphasizing the maximization of resource utilization within time windows and constraints, rather than optimizing driving paths or times. Different scheduling algorithms are introduced by Kuhn and Loth (2009), including one MILP problem based on solving static vehicle scheduling problems within a moving time window. Lastly, in the work of Chen (2022), the main goal is to create an automated task allocation optimization mechanism. Here, an auction mechanism for task allocation is implemented.

VRPs are used in various contexts beyond GSE. Song et al. (2019) tackle a VRPTW problem to optimize vehicle routes for customer service. Arias-Melia et al. (2022) deal with a more complex Vehicle Sharing and Task Allocation Problem (VSTAP) problem, including vehicle sharing, using a heuristic approach for solving larger instances.

2.2. Energy management

Multiple studies address the energy management of GSE. Rensen (2013) develops a framework to assess airport design choices. His work analyzes GSE requirements, distance, operational time, and energy consumption. Gulan et al. (2019) presents an charging algorithm for fully electrified airports, using an scheduling algorithm based on variable pricing. Charging priority is assigned based on State of Charge (SOC) and availability of GSE. Kirca et al. (2020) develops a Multi-Input Multi-Output Airport Energy Management (MIMO-AEM) model for understanding eGSE charging requirements and scheduling. The model optimizes GSE usage, battery pack sizes, and gate scheduling.

For EVs, Clemente et al. (2014) tackles the integration of EVs with the power distribution problem, focusing on coordinated charging to prevent grid disruptions. Keskin et al. (2021) presents a Electric Vehicle Routing Problem with Stochastic Waiting Times (EVRPTW), addressing queuing and recharging times at charging stations using a two-stage MILP program with a simulation-based heuristic.

2.3. Related problems in the aviation industry

Francfort et al. (2007) compare eGSE with conventional GSE, demonstrating that eGSE yields lower operating costs at select U.S. airports. Hannah et al. (2012) create a decision support tool to assess carbon-neutral growth strategies at airports. van Baaren (2019) conduct a feasibility study for fully electric towing systems, finding that they are technically and operationally viable with substantial fuel and emissions savings, although cost and logistical challenges remain. Sznajderman et al. (2022) develop an integrated model for GSE and associated emissions, considering loading and unloading stages, and aircraft service types, accurately replicating GSE movements. Bosma (2022) created a capacity model study for sustainable aircraft refueling service vehicles. And lastly, van Amstel (2023) and Horstmeier (2023) contribute to the field of electric aviation, by optimizing infrastructure and charging scheduling while minimizing costs and addressing renewable energy integration and various aspects of electric aviation adoption, charger types, and spatial considerations. These works provide an interesting look at the electrification of airports in general from a different perspective.

2.4. Comparing the existing works

The previous sections have discussed different works that are considered relevant for this research. An overview of the works on GSE, with a comparison on different aspects, is provided in Table 1. Here, the focus of the studies is denoted by an icon, referring to "optimization of operations" ( ), "energy management" ( ), "operational costs" ( ), or "environmental impact" ( ). In addition, a distinction is made between works that consider GSE or not. It stands out that the vast majority of works that consider GSE only look at one or a few GSE types, and in the works that consider several GSE types, the different properties of these GSE types are not taken into account. In some works, several GSE types are divided into a number of categories with similar properties.

Table 1: A comparison of different studies that include the modeling of GSE operations.

	Kuhn and Loth (2009)	Ip et al. (2013)	Padrón et al. (2016)	Song et al. (2019)	Wang et al. (2021)	Gök et al. (2022)	Zhang et al. (2022)	Arias-Melia et al. (2022)	Chen (2022)	Van Oosterom et al. (2023)	Bao et al. (2023)	Rensen (2013)	Clemente et al. (2014)	Gulan et al. (2019)	Kirca et al. (2020)	Keskin et al. (2021)	Francfort et al. (2007)	Hannah et al. (2012)	Van Baaren (2019)	Sznajderman et al. (2022)	Bosma (2022)	This paper
Focuses on																						
Considers GSE	✓	✓	✓		✓	✓	✓		✓	✓	✓	✓		✓	✓		✓	✓	✓	✓	✓	✓
Includes all common GSE types															✓			✓				✓
- Number of GSE types included	1	0	7	0	1	6	3	0	6	1	1	6	0	6	16	0	3	8	1	11	1	16
- Considers GSE types individually	✓	✓	✓		✓	✓	✓		✓	✓	✓	✓					✓		✓	✓	✓	✓
GSE turnaround operations	✓	✓	✓		✓	✓	✓		✓	✓	✓	✓			✓				✓	✓	✓	✓
- Task allocation	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓								✓		✓	✓
- Travel time between locations	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓			✓			✓	✓	✓	✓
- Service time window	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓										✓
- Service time at aircraft stand	✓	✓	✓		✓	✓	✓		✓	✓	✓	✓			✓				✓	✓	✓	✓
- Individual service times	✓	✓	✓		✓	✓	✓		✓	✓	✓	✓			✓				✓	✓	✓	✓
- Energy consumption of vehicles				✓						✓	✓	✓	✓		✓	✓			✓	✓	✓	✓
Considers eGSE										✓	✓	✓		✓	✓		✓	✓	✓		✓	✓
- Considers mixed fleets											✓			✓	✓			✓			✓	
- Charging (scheduling)										✓	✓		✓	✓	✓	✓			✓		✓	
Determines number of vehicles				✓		✓		✓		✓		✓			✓						✓	✓
Number of vehicles as an input	✓	✓	✓		✓		✓		✓		✓			✓				✓	✓	✓		

3. Conceptual framework

The airport forms an essential part of the air transport system, as it is the physical site at which a modal transfer is made from the air mode to the land modes or vice versa. It accommodates for the interaction of the two other major components of the air transport system, namely: the airline and the user. An airport is designed to enable an aircraft to, if required, unload and load passengers, cargo, and crew (Ashford et al., 2013). These events form the essential parts of the turnaround process of an aircraft. The turnaround process describes all operations for preparing an aircraft for the flight. Aircraft depend on GSE to perform the required processes, such as cleaning, maneuvering and refueling (National Academies of Sciences, Engineering, and Medicine, 2015). Airports that service many yearly passengers must have ground handling service provider(s) that can supply the handling of those passengers and the servicing, maintaining, and engineering of aircraft (Ashford et al., 2013).

The turnaround process is performed during the Ground Time (GT). It starts when an aircraft reaches its parking position at the Actual In Block Time (AIBT) and lasts until the aircraft is ready to depart at the Actual Out Block Time (AOBT) (Schmidt et al., 2016; More and Sharma, 2014; Horstmeier and de Haan, 2001). This is the case for flights that are made ready for take-off immediately after arrival. In general, the servicing time depends on the aircraft type, the number of passengers, the cargo to be (un)loaded as well as the business model of the aircraft operator (Schmidt et al., 2016). An efficient and reliable aircraft turnaround is an essential component of airline success, which allows them to maintain schedules (Schmidt, 2017; Vidosavljevic and Tosic, 2010). In 2019, 32.6% of all flight delays were caused by problems regarding the turnaround of aircraft at airports (Performance Review Commission, 2022). In 2021, this share, which also includes delays related to protective COVID-19 measures, has risen to 47.5%.

The turnaround time has hence become a very important key parameter in determining the profitability of an airline (More and Sharma, 2014).

Each type of GSE has specific properties, activities, and duty cycles. Largely based on the available ACRP reports (National Academies of Sciences, Engineering, and Medicine, 2012, 2015) about GSE, it is possible to classify the GSE types based on their use case: 1.) ground power/air conditioning, 2.) aircraft movement, 3.) aircraft servicing, 4.) passenger (un)loading, and 5.) baggage/cargo handling. The operation of GSE is a function of several parameters that can vary considerably from airport to airport. They influence the type, number and operation (service time) of GSE. A distinction can be made between 1.) operational characteristics, 2.) aircraft characteristics, and 3.) airport infrastructure (ICAO, 2020). Operational procedures determine the types and amounts of GSE services required. The aircraft characteristics influence the stand allocation and often the handling procedures involving GSE. And in terms of airport infrastructure, different aircraft stands exist. They can exhibit considerable differences in terms of location and technical equipment available, which influence the number and operations of GSE. They may also differ for reasons of dedicated usage (e.g. whether a stand is used for cargo aircraft or for passenger aircraft).

As part of noise abatement, night curfews on aircraft operations exist at many airports throughout the world (Ashford et al., 2013). Consequently, many airports only use (the majority of) GSE during the day, meaning they eGSE can and must be charged at night. The consumption of and the way in which the small GSE vehicles are used makes it possible to only have to recharge these vehicles at night, as they can be used for a complete day on one full battery charge. And if it turns out to be necessary, opportunity charging can be used during the day (Timmermans, 2023). Other, larger GSE vehicles, must be charged during the day. With these vehicles, the challenge still lies in battery capacity and the limited space and weight that can be spend on batteries. These vehicles therefore have a greater downtime than their diesel equivalents (Timmermans, 2023).

It has become apparent that there are many differences between the GSE types required for servicing aircraft at an airport. In order to use the proposed model as widely as possible, the model will therefore distinguish between a number of groups with GSE types that share the same properties. Based on literature research and interviews, a number of essential components that are important when modeling GSE operations at an airport can be defined. The literature research shows that there are only a few works that consider multiple GSE types and none of the works that do this do include all details that are assumed to be essential based on the literature research. The smaller GSE types currently do not pose a major challenge in the field of charging. This could possibly be the case in the future for the larger GSE types. Therefore, the model will mainly focus on simulating and optimizing the GSE operations and the associated energy consumption. A follow-up study could then focus on a possible charging strategy based on this energy consumption. In the same way, an addition could be made in the future that would allow mixed fleets to be considered. Including the above elements results in a contribution as shown in the last column of Table 1. Because the literature review also shows that the nature of the operations to be simulated often leads to a computationally complex problem, extensive attention will also be paid to improving the solvability of the model.

4. Problem formulation

4.1. Model setup

The problem at hand will be described as a Task Scheduling Problem (TSP). According to Bunte and Kliewer (2009), an optimal schedule is characterized by minimal fleet size and/or minimal operational costs. These elements are at the heart of the problem. In literature, MILP is widely used to solve TSPs and VRPTWs Bao et al. (2023); Keskin et al. (2021); Kuhn and Loth (2009); Clemente et al. (2014); Wang et al. (2021); Song et al. (2019). Its modeling capability and the availability of good solvers make that MILP is a powerful tool for planning and control problems Earl and D'Andrea (2005). Therefore, the problem at hand will also be solved using MILP.

Within the model there are 1.) parking tasks, 2.) flight tasks and 3.) logistics tasks. The properties of the task types are explained in the work of Timmermans (2023). Two parking tasks are defined for each parking location. The parking task from where a vehicle starts runs from the beginning of the day to the end of the day. This makes it possible for a vehicle to leave a parking location throughout the day. The parking task where a vehicle ends is defined at the end of the day. The flight tasks arise from the flight schedule and the turnaround tables of the aircraft types. The earliest time (ET_i) and latest time (LT_i) of a flight task i define the time window within which the task must be executed. The task time (TT_i) follows from the turnaround table as well. It always holds that $TT_i \leq LT_i - ET_i$. The demand (DEM_i) and energy consumption (EC) of a flight task depend on the aircraft type and the GSE type. One flight may result in multiple flight tasks, based on the required number of vehicles and how long the aircraft is on the ground. The location of a flight task is an aircraft stand. It is therefore possible that there are several flight tasks with the same location if 1.) in the flight schedule several flights are handled on one aircraft stand and/or 2.) several vehicles of one type are required to handle one flight. The logistics tasks may be used by a vehicle to refill or empty its storage compartment. They are therefore only necessary for GSE types with a so-called logistics function. In this paper, the logistics tasks are placed prior to a flight task in terms of time window. This makes it possible for a vehicle to go to a logistics task to refill before a flight, if necessary. The model in this paper can therefore only be used for vehicles that have a decrease in load when servicing a flight.

4.2. Rolling horizon approach

To reduce the computation time for the optimization problem at hand, a rolling horizon is implemented. Kuhn and Loth (2009) use a rolling horizon for the scheduling of GSE as well. Algorithm 1 explains how it is applied in the context of this research. Here CT is the current time and Π is the set of flight tasks that still need to be assigned. The set of all flight tasks is A. Each iteration set F is defined as the set of flights $i \in \Pi$ that have an earliest time (ET_i) that is within the next $t_{forward}$ minutes from the current time (CT). The optimization problem is then solved, which uses the data from the vehicles $k \in K$ and the flight tasks $i \in F$ to perform the assignment of tasks. The assigned flight tasks with a start time (s_i) that is within the current time and the time step at which the update takes place, t_{update}, are added to set Ω. Here, it holds that $t_{update} \leq t_{forward}$. The execution of the flight tasks in Ω is fixed and removed from set Π. The overall task list is updated and the current time is increased with t_{update}. After this, set F is defined again, based on the new CT. This process repeats until $\Pi = \emptyset$.

Algorithm 1: Rolling horizon approach

$CT \leftarrow 0$
$\Pi \leftarrow A$
while $\Pi \neq \emptyset$ **do**
  $F \leftarrow \{i \in \Pi : ET_i \leq CT + t_{forward}\}$
  Solve: optimization problem using data regarding all $k \in K$ and $i \in F$
  $\Omega \leftarrow \{i \in F : s_i \leq CT + t_{update}\}$
  Assign: all tasks in Ω
  $\Pi \leftarrow \Pi \setminus \Omega$
  Update: overall task list together with vehicles states and SOC
  $CT \leftarrow CT + t_{update}$

4.3. Mathematical model

The notations used in this paper are shown in Table 2. In the sets used in the model, a distinction is made between numerical sets and modeling sets. For the modeling sets, the model formulation sometimes uses one or more subscripts, which indicate a subset. Three subscripts can be distinguished: 1.) S (start), for the tasks that need to be used as start tasks, 2.) B (between), for the tasks that can be used in between, and 3.) E (end), for the tasks that need to be used as end tasks. For example, P_S is a subset of set P, i.e.

Table 2: Notations used in this paper.

Set	Description	
$\mathbb{R}^+$	Set of all positive real numbers	
$\mathbb{R}_0^+$	Set of all positive real numbers including 0	
$\mathbb{N}_0^+$	Set of all positive integers including 0	
P	Set of parking tasks	
F	Set of flight tasks	
L	Set of logistics tasks	
T	Set of all tasks ($P \cup F \cup L$)	
K	Set of all vehicles ($K_{unused} \cup K_{used}$)	
K_{unused}	Set of vehicles that have not been used yet ($K_{unused} \subseteq K$)	
K_{used}	Set of vehicles that have been used in a previous run ($K_{used} \subseteq K$)	
$K_{depleted}$	Set of vehicles that are used and depleted ($K_{depleted} \subseteq K_{used}$)	
Index	**Description**	
i	Index for current task	$i \in T$
j	Index for the next task	$j \in T$
k	Index for vehicle	$k \in K$
Parameter	**Description**	**Domain**
ET_i	Earliest time of performing task i	$\mathbb{R}_0^+$
LT_i	Latest time of performing task i	$\mathbb{R}^+$
TT_i	Required time for task i	$\mathbb{R}_0^+$
D_{ij}	Distance between task i and j	$\mathbb{R}_0^+$
V	Travel speed of vehicles	$\mathbb{R}^+$
RT_k	Time at which vehicle k becomes ready	$\mathbb{R}_0^+$
ST_k	Starting task of vehicle k	T
SL_k	Starting load of vehicle k	$\mathbb{R}_0^+$
EP_k	Ending parking task of vehicle k in previous run	P
LOC_i	Location number of task i	$\mathbb{N}_0^+$
TN_i	Task name of task i	-
DEM_i	Demand of task i	$\mathbb{R}_0^+$
C	Capacity of vehicles	$\mathbb{N}_0^+$
R	Logistics refilling time constant	$\mathbb{R}^+$
M	Big M for time constraints	$\mathbb{R}^+$
Q	Big M for capacity constraints	$\mathbb{R}^+$
Variable	**Description**	**Domain**
x_{ij}	Whether a vehicle travels from task i to j	$\{0,1\}$
y_i	Whether task i is visited	$\{0,1\}$
z_k	Whether vehicle k is used	$\{0,1\}$
s_i	Starting time of servicing task i	$\mathbb{R}_0^+$
w_i	Waiting time at task i	$\mathbb{R}_0^+$
q_i	Load quantity of a vehicle after visiting task i	$\mathbb{N}_0^+$

$P_S \subset P$, and it contains all task indices of parking tasks that need to be used as start tasks. If no subscript is indicated, the entire set is meant (e.g. $P_{SBE} = P$). After each optimization, the modeling sets P, F, L, K_{unused}, K_{used} and $K_{depleted}$ are updated as part of the rolling horizon. After each optimization during the rolling horizon, a number of parameters are updated based on the previous optimization. This concerns parameters RT_k, ST_k, SL_k, EP_k, and LOC_i.

The objective function consists of five parts: 1.) the total number of vehicles used, 2.) the total distance traveled by all vehicles (in km), 3.) the number of times vehicles went to a logistics task, 4.) the sum of the starting times at the flight tasks and 5.) the total waiting time of vehicles at a logistics task. Objective function components 1 and 2 are used to optimize actual scenarios and components 3, 4 and 5 are used to help the MILP's solver converge to a solution. Depending on the goal of the optimization, the weighting factors λ_1 to λ_5 can be used to determine the proportions of the five objective function components. However, the weighting factors λ_3 to λ_5 must be relatively small so that they do not influence the optimization of the first two objective function components.

$$\min \lambda_1 \underbrace{\left(\sum_{k\in K} z_k\right)}_{\text{obj1}} + \lambda_2 \underbrace{\left(\sum_{i\in T}\sum_{j\in T} \frac{D_{ij}}{1000} x_{ij}\right)}_{\text{obj2}} + \lambda_3 \underbrace{\left(\sum_{i\in F} s_i\right)}_{\text{obj3}} + \lambda_4 \underbrace{\left(\sum_{i\in T\setminus L}\sum_{j\in L} x_{ij}\right)}_{\text{obj4}} + \lambda_5 \underbrace{\left(\sum_{i\in L} w_i\right)}_{\text{obj5}}$$

Subject to

$$y_j = \sum_{i\in T} x_{ij} \qquad \forall j \in T_{BE} \tag{G1b}$$

$$y_i = \sum_{j\in T} x_{ij} \qquad \forall i \in T_S \tag{G1b}$$

$$z_k \geq y_i \qquad \forall k \in K,\ i = ST_k \tag{G2}$$

$$\sum_{i\in T} x_{ih} = \sum_{j\in T} x_{hj} \qquad \forall h \in T_B \tag{G3}$$

$$\sum_{i \in T} x_{ij} \leq 1 \qquad \forall j \in T \tag{G4a}$$

$$\sum_{j \in T} x_{ij} \leq 1 \qquad \forall i \in T \tag{G4b}$$

$$x_{ii} = 0 \qquad \forall i \in T \tag{G5}$$

$$x_{ij} = 0 \qquad \forall i \in T,\ \ j \in T_S \tag{G6a}$$

$$x_{ij} = 0 \qquad \forall i \in T_E,\ \ j \in T \tag{G6b}$$

$$x_{ij} = 0 \qquad \forall i \in T_S,\ \ j \in T_E \tag{G7}$$

Constraints G1b and G1b connect x_{ij} to y_i. Constraint G2 ensures that $z_k = 1$ if vehicle k is used for a task in F. Constraint G3 ensures the flow conservation for tasks in T_B. Constraints G4a and G4b ensure that task j can only be visited once and task i can only be left once, respectively. Constraint G5 ensures that vehicles do not drive from task i to task i. Constraints G6a and G6b ensure that a vehicle can not enter a start task and leave an end task, respectively. Constraint G7 ensures that a vehicle can not travel from a start to an end task.

$$s_i \geq ET_i \qquad \forall i \in T \tag{G8a}$$

$$s_i \leq LT_i \qquad \forall i \in T \tag{G8b}$$

$$s_j \geq s_i + TT_i + w_i + \frac{D_{ij}}{V} - M\left(1 - x_{ij}\right) \qquad \forall i, j \in T,\ \ i \neq j \tag{G9a}$$

$$s_j \leq s_i + TT_i + w_i + \frac{D_{ij}}{V} + M\left(1 - x_{ij}\right) \qquad \forall i, j \in T,\ \ i \neq j \tag{G9b}$$

$$s_j \geq \left(RT_k + \frac{D_{ij}}{V}\right) x_{ij} \qquad \forall j \in T,\ \ i = ST_k,\ \ k = LOC_i \tag{G10}$$

Constraints G8a and G8b ensure that visiting a task can not start before ET_i or after LT_i, respectively. Constraints G9a and G9b ensure that a vehicle can not start with task j before arriving at task j. Constraint G10 ensures that a vehicle does not start the servicing of task j before it arrives there (when traveling from starting task i).

$$z_k \leq z_l \qquad \forall k \in K_{unused},\ \ l \in K_{used} \tag{G11}$$

$$y_i \leq y_h \qquad \forall k \in K,\ \ i = EP_k,\ \ h = ST_k \tag{G12}$$

$$z_k = 0 \qquad \forall k \in K_{depleted} \tag{G13}$$

Constraint G11 ensures that unused vehicles can only be used if all previously used vehicles are used again. Constraint G12 ensures that an end parking task can only be used if the vehicle that ended there in a previous run is used in the current run. Constraint G13 ensures that depleted vehicles are not used.

$$y_i = 1 \qquad \forall i \in F \tag{F1}$$

$$s_i \geq ET_i \qquad \forall i \in F \tag{F2a}$$

$$s_i \leq LT_i - TT_i \qquad \forall i \in F \tag{F2b}$$

Constraint F1 ensures that all flight tasks are performed. Constraints F2a and F2b ensure that performing task i can not start before ET_i or end after LT_i, respectively.

$$q_j \leq q_i - DEM_j + Q\left(1 - x_{ij}\right) \qquad \forall i \in T,\ \ j \in T \setminus L,\ \ i \neq j \tag{L1a}$$

$$q_j \geq q_i - DEM_j - Q\left(1 - x_{ij}\right) \qquad \forall i \in T,\ \ j \in T \setminus L,\ \ i \neq j \tag{L1b}$$

$$q_i \geq C - Q\left(1 - x_{ij}\right) \qquad \forall i \in L,\ \ j \in T \setminus L \tag{L2}$$

$$q_i \geq SL_k \qquad \forall i \in T_s,\ \ k = LOC_i \tag{L3a}$$

$$q_i \leq SL_k \qquad \forall i \in T_s,\ \ k = LOC_i \tag{L3b}$$

Constraints L1a and L1b ensure that the load of a vehicle at task j is equal to the load at task i minus the demand of task j. Constraint L2 ensures that a vehicle leaves the logistics task with a full load. Constraints L3a and L3b ensure that vehicle k leaves the starting task with a load of SL_k.

$$w_j \geq R\left(q_j - q_i\right) - M\left(1 - x_{ij}\right) \qquad \forall i \in T,\ \ j \in L \tag{L4}$$

$$s_i + w_i \leq LT_i \qquad \forall i \in L \tag{L5}$$

Constraint L4 ensures that the waiting time at a logistics task is R minutes per load unit that is added. Constraint L5 ensures that a vehicle leaves a logistics task before LT_i.

$$q_i \leq C \qquad \forall i \in T \tag{L6}$$

$$x_{ij} = 0 \qquad \forall i, j \in L \tag{L7}$$

$$x_{ij} = 0 \qquad \forall i \in L,\ \ j \in F,\ \ TN_i \neq TN_j \tag{L8}$$

$$x_{ij} = 0 \qquad \forall i \in L,\ \ j \in P \tag{L9}$$

Constraint L6 ensures that the load of a vehicle can not exceed the vehicle's capacity. Constraint L7 ensures that vehicles do not drive from one logistics task to another. Constraint L8 ensures that vehicles can only drive from a logistics task to its corresponding flight task. Constraint L9 ensures that vehicles can not drive from a logistics task to a parking task.

5. Model solving

Although mathematically correct, the model's solvability can be substantially improved by several measures. Powerful software packages can solve MILP-problems efficiently for problems in which the number of binary variables is of reasonable size (Earl and D'Andrea, 2005). A major disadvantage of MILP is its computational complexity. The NP-complete nature of many scheduling problems, and MILP-models in general, precludes their being solved within a reasonable time (Roslöf et al., 2002). According to Earl and D'Andrea (2005), the computational requirements can grow significantly as the number of binary variables needed to model the problem increases. Darvish et al. (2020) state that the effectiveness of solving optimization problems using a brand-and-bound/cut algorithm relies mainly on its mathematical formulation. Therefore, several improvements are implemented such as model tightening, increasing the model density, and breaking model symmetry.

5.1. Model tightness

The constraints below are mathematically redundant, but improve the solvability by enforcing variable upper bounds on each continuous variable to tighten the feasible region.

$$s_i \leq ET_i + M\,(1 - y_i) \qquad \forall i \in P_S \tag{T1}$$

$$s_i \leq ET_i + M\,(1 - y_i) \qquad \forall i \in P_E \tag{T2}$$

Constraint T1 forces a vehicle to start at ET at the start P task that is used. Constraint T2 forces a vehicle to arrive at its end P task at ET.

5.2. Model density

Although there is nothing wrong with the model formulation from a mathematical point of view, the model does contain a lot of binary variables that could never be part of a feasible solution due to the constraints in the model. This makes that the model is currently quite sparse.

In a similar way to the chain decomposition applied in the work of Hooker and Natraj (1995), by filtering the (i, j)-pairs based on the constraints of the model, it is already possible to omit a large number of (i, j)-pairs from the model in advance. This reduction does not affect the availability of potentially optimal solutions in the model, because only those decisions that are infeasible due to the constraints are omitted from the model. The reduction can go up to $> 85\%$. Let T be the set of tasks, and G_0 be the set of all pairs (i, j), i.e. $G_0 = \{\ (i, j)\ \mid i, j \in T\ \}$. Then, the steps to reduce the (i, j)-pairs are:

$$\begin{aligned}
G_1 &= G_0 \setminus \{\ (i, j)\ \mid i, j \in G_0, i = j\ \} \\
G_2 &= G_1 \setminus \{\ (i, j) \mid i, j \in G_1, i \in L, j \in F, \\
&\qquad\qquad\qquad\qquad TN_i \neq TN_j \} \\
G_3 &= G_2 \setminus \{\ (i, j)\ \mid i, j \in G_2, j \in T_S\ \} \\
G_4 &= G_3 \setminus \{\ (i, j)\ \mid i, j \in G_3, i \in T_E\ \} \\
G_5 &= G_4 \setminus \{\ (i, j)\ \mid i, j \in G_4, i, j \in L\ \} \\
G_6 &= G_5 \setminus \{\ (i, j)\ \mid i, j \in G_5, i \in L, j \in P\ \} \\
G_7 &= G_6 \setminus \{\ (i, j)\ \mid i, j \in G_6, i \in T_S, j \in T_E\ \} \\
G_8 &= G_7 \Big\backslash \Big\{\ (i, j)\ \Big|\ i, j \in G_7, ET_i + TT_i + \\
&\qquad\qquad\qquad \frac{D_{ij}}{V} > LT_j - TT_j \Big\}
\end{aligned}$$

The set G_8 represents the filtered combinations after applying all the specified conditions.

To further reduce the number of variables in the model, logistics tasks are only created for vehicles with a logistics task. For vehicles without a logistics task it holds that $L = \emptyset$. The decision variable q_i and the "logistics task constraints" are also only added to the model if necessary. The above actions result in a lower computational load in two ways: 1.) when creating the model there are fewer constraints and variables that have to be included, and 2.) because the optimization problem is smaller, it can be solved faster.

5.3. Model symmetry

Degeneracy in MILP problems occurs when the optimal solution to the problem lies at a point where one or more of the binary variables can take on different values while still maintaining the same optimal objective value. In other words, there are multiple feasible solutions that all yield the same objective function value. These solutions are called symmetric. When degeneracy occurs, it means that the search space for finding the optimal integer solution is more complex and may require additional computational effort to explore all possible integer combinations. It has been a topic of interest since the invention of the simplex method (Gamrath et al., 2020). By augmenting the model with suitable symmetry-breaking constraints, the structure of the model can be considerably improved by reducing the extent of the feasible region that must be explored (Sherali and Smith, 2001).

In the developed model, degeneracy is resulting from the possible combinations to assign vehicles to a sequence of tasks. For a given vehicle set with $|K|$ vehicles, there are

$$C\left(|K|, N_u\right) = \binom{|K|}{N_u} = \frac{|K|!}{N_u!\left(|K| - N_u\right)!}$$

possible options to select N_u vehicles from the fleet. Second, among the selected vehicles, there are $N_u!$ options to allocate the sequences of tasks to the vehicles. Combining both types of symmetry results in

$$\binom{|K|}{N_u} N_u! = \frac{|K|!}{N_u!\left(|K| - N_u\right)!} N_u! = \frac{|K|!}{\left(|K| - N_u\right)!}$$

equivalent solutions.

To break the first type of symmetry, a constraint based on the work of Adulyasak et al. (2014) can be used: constraint S1 ensures that vehicle k can only be used if vehicle $k-1$ is used.

$$z_k \leq z_{k-1} \qquad \forall k \in K_{unused} \setminus \min\left(K_{unused}\right) \tag{S1}$$

To resolve the second symmetry issue, a hierarchical constraint inspired by Darvish et al. (2020) can be used: constraint S2 ensures that if task $j \in T_B$ is serviced by vehicle k, then at least one other task $j' \in T_B$, with $j' < j$, must be performed by vehicle $k-1$.

$$\begin{aligned} & x_{ij} \leq \sum_{j'=\min T_B}^{j-1} x_{i'j'} \\ & \forall j \in T_B,\ \ k \in K_{unused} \setminus \min\left(K_{unused}\right), \\ & k' \in K_{unused},\ \ k' = k-1,\ \ i = ST_k,\ \ i' = ST_{k'} \end{aligned} \tag{S2}$$

Both constraints are valid inequalities and strengthen the model formulation. These constraints can only be used if all vehicles in the fleet are homogeneous and start at the same location. If this is not the case, a more optimal solution could be prevented by one of the symmetry breaking constraints. The constraints are therefore only applied in the model if this is possible without excluding optimal solutions.

6. Model application

To validate the model, a sensitivity analysis and a case study were conducted based on the GSE fleet of KLM Royal Dutch Airlines that is operating at Amsterdam Airport Schiphol (AAS). To this extent, the MILP-problem was coded in Python and solved using Gurobi. This paper includes the validation for a GSE type without a logistics function (belt loader) and a summary of the results for a GSE type with a logistics function (water truck). We refer to Timmermans (2023) for the complete model validation.

6.1. Instances generation

The following datasets were used to generate the instances:

- Flight schedule: the used flight schedule was provided by KLM and based on the IATA Busy Day definition. Based on this definition, July 13 2023 was selected as the IATA Busy Day. Filtering the flight schedule on airlines that are handled by KLM resulted in a flight schedule with a total of 735 Air Traffic Movements (ATMs) by fourteen different aircraft types. The ATMs were matched with each other to create a flight schedule.

- Task information: The turnaround tables available at KLM for the various aircraft types were used to create the flight tasks. For aircraft types for which no turnaround table was available, a comparable aircraft type was used. A distinction was made between separate arrivals, separate departures and full turnarounds.

- Distances: the aircraft stands and parking locations are divided over 35 location groups. These location groups were based on a document used by KLM. It also includes the distances between the location groups and based on this the shortest distance between all combinations of location groups were calculated.

- Vehicle data: spec sheets by TLD (2023) and Charlatte (2017) were used for the belt loaders and spec sheets by Vestergaard (2023) and Orientitan Ground Support Equipment (2019) were used for the water trucks. The calculation proposed by Kirca et al. (2020) was used for the energy consumption of both vehicles. An average speed of 15 km/h was assumed for the driving speed.

For the sensitivity analysis, the objective function as discussed in Section 4 was first normalized. In this way, the sensitivity analysis is performed across the relevant range of the objective values. Only the first two sub-objectives were considered, which focus on minimizing the number of vehicles used and the distance driven.

6.2. Results for the belt loaders

Figure 1 shows the results of the sensitivity analysis for the belt loaders. A distinction is made between the total number of vehicles used in a day and the maximum number of vehicles required within a 30-minute time window. A number of interesting solutions are:

- Solution 6 with $(\lambda_1, \lambda_2) = (0.70, 0.30)$: This is the solution that requires the least number of vehicles, with the lowest total traveled distance (48.773 km) based on this number of vehicles. In this case, a total of 37 vehicles are used during the day. These vehicles are also all needed at the peak time.

- Solution 10 with $(\lambda_1, \lambda_2) = (0.50, 0.50)$: This solution shows that with 37 vehicles during the peak a lower total traveled distance of 40.733 km can also be achieved. A total of 41 vehicles is used during the day.

- Solution 18 with $(\lambda_1, \lambda_2) = (0.001, 1.00)$: This is the solution with the lowest total traveled distance (24.620 km). This requires a total of 52 vehicles. During the peak, 41 of these vehicles are used.

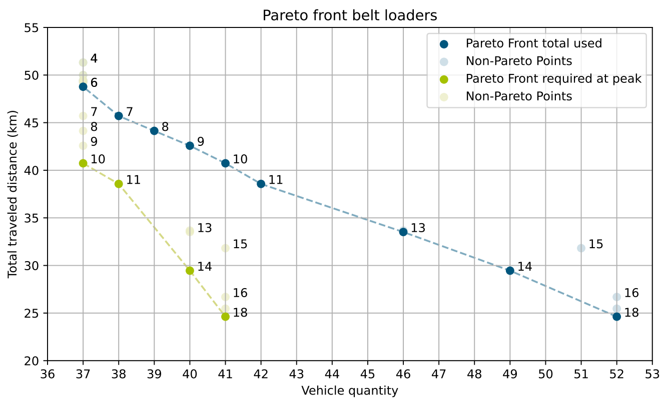

Figure 1: Two Pareto-fronts for the sensitivity analysis of the multi-objective optimization for the belt loader operations. The numbered labels next to the data points correspond to a combination of λ_1 and λ_2.

In general, there is a trend that shows that the use of more vehicles results in a lower total traveled distance. Because this type of GSE only operates at the aircraft stands, the vehicles can often remain idle nearby. The figure also includes solutions that are not in the Pareto front. Analysis of the results has shown that these solutions include inefficiencies that arise from the use of the rolling horizon approach. In these scenarios, a "choice" is made for certain vehicles in one optimization run that is optimal at that moment. However, this choice appears to be generally not optimal in the optimization runs in the remainder of the rolling horizon approach.

Solution 6 from Figure 1 is used for the model validation. Figure 2 shows how many vehicles are needed at each time of the day. The average utilization rate of the vehicles is approximately 21%. Here, the utilization rate is calculated as the total time that a vehicle is busy with (driving to) a task, divided by the time in one day (24 hours). This shows that there is room for charging in between. A total of 210 kWh was used to execute the task schedule. Of this, 182 kWh (86%) was used to perform the tasks on the aircraft stands, i.e. running the conveyor belt, and 29 kWh (14%) was used for driving a total distance of 48.773 km. This makes clear that most of the energy consumption for the belt loaders cannot be optimized, because the flight tasks have to be carried out anyway. If desired, the 29 kWh can be reduced by using more vehicles, as can be seen in Figure 1. None of the belt loaders had an depleted battery at the end of the day.

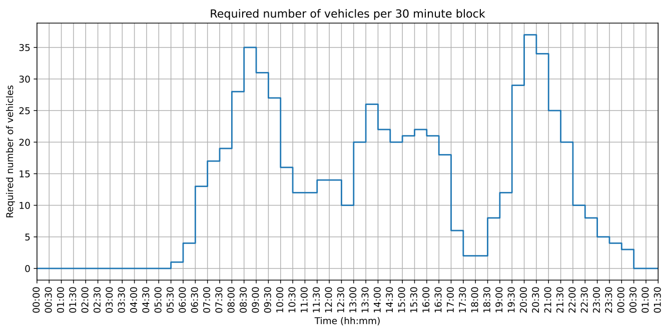

Figure 2: The required number of belt loaders per 30 minutes.

6.3. Validation for the belt loaders

The data available at KLM showed that the number of belt loaders as determined by the model is a bit too high, but in the right order of magnitude. This is mainly due to the fact that two belt loaders are used per flight in the model and in reality this is sometimes one because of 1.) the amount of baggage on a flight, and 2.) the availability of resources. The conversations with KLM also revealed that it is usually not necessary to charge the belt loaders during the day. This is confirmed by the solution of the model. The vehicles were originally purchased with a battery capacity that should last two shifts to operate a full day, but due to degeneration there are batteries that have an State of Health (SOH) that is lower than the 100% used in this model.

6.4. Results for the water trucks

Figure 3 shows the results of the sensitivity analysis for the water trucks. The vast majority of solutions are not part of the Pareto front. A trend that can be deduced from this is that a minimization of total traveled distance in this case also results in a minimization of the number of vehicles required. Because the water trucks first have to go to the logistics location to collect water, a relatively high initial "fixed" distance is required to put a new vehicle into use.

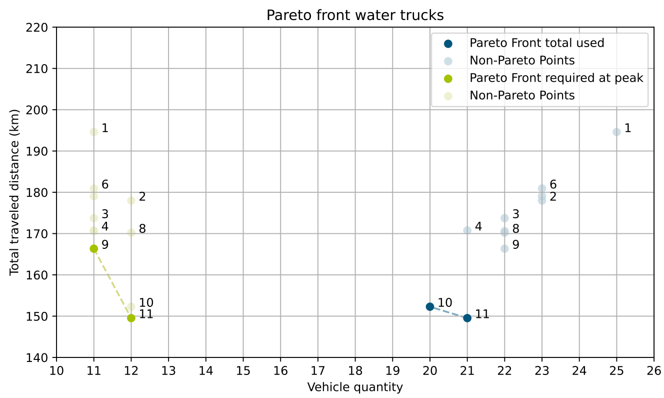

Figure 3: Two Pareto-fronts for the sensitivity analysis of the multi-objective optimization for the water truck operations. The numbered labels next to the data points correspond to a combination of λ_1 and λ_2.

The task schedule that follows from the model for solution 10 (in Figure 3) is shown in Figure 4. New vehicles are added gradually during the day, because other vehicles get depleted. For many vehicles, a time window can be identified in which it would be possible to use opportunity charging. This would result in fewer vehicles needed in total.

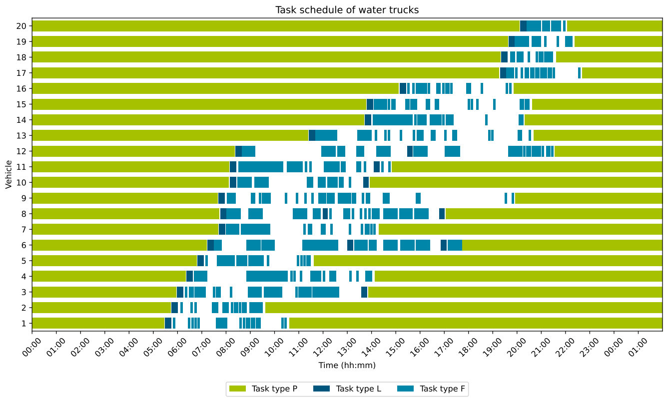

Figure 4: The task schedule for the water truck operations.

A total of 977 kWh was used to execute the task schedule in Figure 4. Of this, 30 kWh (3%) was used to perform the tasks on the aircraft stands, i.e. operating the pump, and 947 kWh (97%) was used for driving a total distance of 152.283 km. This makes clear that most of the energy can be optimized, by minimizing the total traveled distance. The batteries of 16 water trucks were eventually depleted ($SOC < 30\%$).

7. Discussion

Based on the literature review, it had already been established that there are many differences between the GSE types required for servicing aircraft at an airport. Based on this, the decision was made to differentiate certain groups of GSE types in the model that share similar characteristics, so that the model can be broadly applied. This decision was made because the literature review also revealed that there are few works that encompass all GSE types in the research. The results obtained from the model provide a good indication of the required number of vehicles, energy consumption, and the possibility of optimization. However, the validation of the model, in particular, shows that despite distinguishing between certain groups of GSE, there are still differences in the operation and performance of each individual GSE type that affect the results. This is where the desired application of the model becomes relevant. Making a distinction between a strategic and operational application of the model and the associated choices allows for an interpretation of the choices and assumptions that emerged in the review of the existing works and the contributions and limitations of this research.

The results of the model developed in this research show that the model can be used for making strategic decisions. The vehicle quantities generated by the model are in the right order of magnitude, and the total energy consumption provides sufficient insight for making decisions at a strategic level. By including all the components that were assumed to be essential for modeling GSE operations based on the literature review and interviews, the current model can already be used at an operational decision level more effectively than comparable works that have made more simplifications and assumptions at this level.

8. Conclusions and future work

From the results of the case study, it can be concluded that the impact of implementing eGSE on the capacity and demand of a GSE fleet depends on the type of GSE. For GSE types that can last an entire day on a single battery charge, there is no difference in the capacity that can be achieved. These vehicles can, therefore, be directly replaced one-to-one compared to their conventional counterparts. This primarily applies to smaller vehicles, and a condition for this is that the vehicles are not needed at night, which allows them to get charged again. This is the case at many airports due to nighttime curfews.

However, there is also a group of GSE types where the model results show that the vehicles become depleted before the end of the day. To maintain the capacity of these GSE types, it is necessary to either 1.) use more of these vehicles, 2.) charge the vehicles during the day, 3.) use batteries with a higher capacity, or 4.) use vehicles with a better efficiency. However, it should be noted that charging the vehicles during the day does not necessarily results in a maintained capacity, as this is depending on the possibility to charge. This is related to the distribution of the tasks over the day. Using the developed model, it is possible to determine how many additional vehicles are needed when there is no daytime charging. For interim charging, an estimate can be made based on the model results and the concept of opportunity charging, but optimality is not guaranteed in this case. Therefore, additional research is required for these vehicles, including the development of a charging strategy as part of the scope. The work of van Oosterom et al. (2023) provides a nice example of a method for routing the vehicles and scheduling them to either perform flight tasks or battery recharging.

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