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The impact of transitioning to electric Ground Support Equipment on the fleet capacity and energy demand at airports

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ABSTRACT

Airports and airlines are examining and committing to the electrification of Ground Support Equipment (GSE). In line with this trend, in this paper, we develop a model to simulate and optimize the GSE operations at airports. The aim is to estimate the required quantity of eGSE, the charging requirements of eGSE, the change in airport electricity requirements, and the scheduling possibilities of eGSE charging for the existing turnaround procedures. This is done by means of a Task Scheduling Problem (TSP), that is optimized using Mixed-Integer Linear Programming (MILP). A case study is performed on KLM's GSE fleet at Amsterdam Airport Schiphol. Based on this, it is concluded that daily operations can be sustained without increasing fleet size for GSE types capable of lasting a full day on a single charge, assuming vehicles can recharge overnight. This is the case at many airports due to nighttime curfews. The operational procedures used by the handler play a key role in achieving this outcome. The results confirm that the model is suitable for strategic decision-making and it is effective at the operational level. The model has the potential to lead to a more efficient use of resources in the operation.

1. Introduction

1.1. Background and motivation

In 2017, the aviation sector was the second-largest source of Greenhouse Gas (GHG) emissions in the transport sector after road traffic (European Commission, 2021). This environmental impact is expected to grow, as traffic increases are outpacing fuel efficiency improvements and emission reductions from other sectors (European Union Aviation Safety Agency, 2022). To mitigate climate change, the aviation sector must reduce GHG emissions, like CO_2, and other air pollutants from fossil fuels. Most aviation-related carbon emissions stem from aircraft operations (Kirca et al., 2020), prompting several initiatives for low-emission aircraft (Brelje and Martins, 2019; Adeoye, 2025). Ground Support Equipment (GSE), though smaller in share, also contributes significantly to carbon and NO_x emissions in the aviation sector (National Academies of Sciences, Engineering, and Medicine, 2015; Kirca et al., 2020; Bahman, 2023; Adeoye, 2025; Akande, 2025), accounting for 13% of NO_x at U.S. airports in 2012 (Benosa et al., 2018). GSE supports the turnaround process of aircraft between arrival and departure at an airport (National Academies of Sciences, Engineering, and Medicine, 2015). Transitioning to low or zero-emission GSE and supporting infrastructure can significantly reduce airport-related emissions (Kirca et al., 2020; Alruwaili and Cipcigan, 2022). Full electrification could cut GSE emissions by over 90% compared to diesel use (Akande, 2025), and potentially prevent 28% of early deaths from airport emissions in the UK (Yim et al., 2013). Hence, airports and airlines are examining and committing to the electrification of GSE (Francfort et al., 2007; Kirca et al., 2020; Hájnik et al., 2021; Xiang et al., 2021; Soares and Wang, 2021; Adeoye, 2025; Miller and Rutledge, 2025).

1.2. Problem statement and research question

Despite the potential of electric GSE (eGSE), several challenges arise in its deployment. The two main challenges pertain to the significantly longer charging time compared to refueling conventional fossil-fueled vehicles and the increased burden on the electric grid (Gulan et al., 2019; Xiang et al., 2021). According to Bao et al. (2023), the electrification of airports can increase flight delays at smaller airports with

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less flexible networks. Next to this, many airports currently do not have the power generation capability or electrical infrastructure required to support the electrification plans of the future (Miller and Rutledge, 2025). And while electric models are available for smaller types of GSE, larger variants remain under development (Timmermans, 2023). These challenges create uncertainty in the early stage decision-making of different stakeholders, such as airport operators, ground service providers, and airline companies, who need to assess the implications of transitioning to eGSE. For effective planning it is therefore important to be able to estimate (1.) the required quantity of eGSE, (2.) the charging requirements of eGSE, (3.) the change in airport electricity requirements, and (4.) the scheduling possibilities of eGSE charging for the existing turnaround procedures. To address these needs, this study aims to answer the main research question: What is the impact of the implementation of eGSE when optimizing the capacity and demand of GSE fleets?

1.3. Research contribution and significance

The primary contribution of this research is the development of a model that offers operational insights into the deployment of eGSE at airports. The transition to low-emission GSE alternatives presents challenges related to (high initial) costs, (charging) infrastructure, and operational range limitations (Soares and Wang, 2021; Adeoye, 2025; Akande, 2025). The model addresses these by providing estimates on fleet sizing, charging infrastructure needs, energy requirements, and scheduling strategies, aiding early-stage decision-making. It is applied to a real-world case for KLM Royal Dutch Airlines at Amsterdam Airport Schiphol (AAS), demonstrating its practical relevance. This data-driven approach for decarbonizing ground operations informs infrastructure planning and investment decisions, which is essential, given the critical need to explore alternative energy sources for GSE (Bahman, 2023).

This paper is organized as follows: Section 2 reviews the relevant literature, followed by the background of eGSE (operations) in Section 3. After that, the problem is formulated in Section 4, with complexity reduction measures in Section 5. Section 6 presents the case study, and the results are discussed in Section 7. Finally, conclusions and future research lines are provided in Section 8.

2. Literature review

This section reviews the existing literature on (e)GSE that is considered relevant for this research. The scientific contribution of this work is provided in Section 2.5.

2.1. Optimization of operations

Scheduling GSE for airport operations is often treated as a VRPTW (Vehicle Routing Problem with Time Windows). Different scheduling algorithms are introduced by Kuhn and Loth (2009), including one Mixed-Integer Linear Programming (MILP) problem based on solving static vehicle scheduling problems within a moving time window. Padrón et al. (2016) address this problem with a distinct VRPTW for each vehicle, 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) formulate the problem as a MILP model. Gök et al. (2022) and Zhang et al. (2022) treat the problem as a Resource-Constrained Project Scheduling Problem (RCPSP) instead of a VRP. The work of Gök et al. (2022) focuses on aircraft turnaround tasks and staff routing, while the work of Zhang et al. (2022) emphasizes the maximization of resource utilization within time windows and constraints, in the context of military aircraft handling.

Several works are focusing on (electric) aircraft towing tractors. van Oosterom et al. (2023) 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. A VRPTW formulation is presented by Bao et al. (2023), who establish a model for mixed fleets of aircraft towing tractors. Ahmadi and Akgunduz (2023) discuss the electrification of taxiing operations and optimize these using a MILP model, minimizing taxiing time, ground delays and fuel consumption. Zoutendijk et al. (2023) review existing works on operational aspects of electric towing of aircraft. The work summarizes the main research directions needed to support the large-scale implementation of electric aircraft towing vehicles in the next few decades.

Alonso Tabares et al. (2021) propose a ground handling management structure compatible with increased ground handling automation. A mathematical formulation of the GSE location and assignment problem has been formulated that is applicable for multiple GSE types, including non-motorized equipment. Saggar et al. (2021) propose a booking mechanism to allow airlines to book GSE in advance. The results show that the booking concept has potential to enhance apron operations, by improving on some key metrics such as average turnaround delay.

2.2. Energy management

Multiple studies address the energy management of GSE. Gulan et al. (2019) present a charging algorithm for fully electrified airports, using a scheduling algorithm based on variable pricing. Charging priority is assigned based on State of Charge (SOC) and availability of GSE. Kirca et al. (2020) develop 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. Alruwaili and Cipcigan (2022) propose a methodology for using eGSE to participate in the frequency regulation market. They show that eGSE can support the power grid by offering flexible V2G services.

Xiang et al. (2021) conduct a techno-economic analysis of a hydrogen-solar-storage integrated energy system for airport electrification. By using a flight schedule, a load model is developed, including electric aircraft and eGSE charging profiles. Based on this, an airport microgrid is optimized using a MILP model. Miller and Rutledge (2025) also discuss airport electrification and demonstrate that microgrids may be a practical solution for airports to reach their electrification goals.

2.3. Operational costs

Salihu et al. (2021) develop a discrete event simulation (DES) and cost model to develop an annual cost estimate for using electric towing tractors. Their findings show significant potential for reducing fuel consumption and emissions. Soares and Wang (2021) conduct a life-cycle cost analysis (LCCA) to compare eGSE with conventional GSE. They compare different charging systems. They show that the conventional option initially requires less investment, but it costs more over its lifetime. Sari et al. (2022) conduct a benefit cost analysis (BCA) and show that both conventional and electric GSE are feasible investments. The use of conventional GSE is considered more profitable when assuming 25 years of use.

2.4. Environmental impact

Van Baaren and Roling (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) creates a capacity model

Table 1
A comparison of different studies on GSE, based on several key components.

	Kuhn and Loth (2009)	Padrón et al. (2016)	Wang et al. (2021)	Alonso Tabares et al. (2021)	Saggar et al. (2021)	Gök et al. (2022)	Zhang et al. (2022)	van Oosterom et al. (2023)	Ahmadi and Akgunduz (2023)	Bao et al. (2023)	Gulan et al. (2019)	Kirca et al. (2020)	Xiang et al. (2021)	Alruwaili and Cipcigan (2022)	Salihu et al. (2021)	Soares and Wang (2021)	Sari et al. (2022)	Van Baaren and Roling (2019)	Sznajderman et al. (2022)	Bosma (2022)	Adeoye (2025)	This paper
Focuses on[a]	optimization of operations	optimization of operations	optimization of operations	optimization of operations	optimization of operations	optimization of operations	optimization of operations	optimization of operations	optimization of operations	optimization of operations	energy management	energy management	energy management	energy management	operational costs	operational costs	operational costs	environmental impact	environmental impact	environmental impact	environmental impact	optimization of operations
Includes multiple GSE types		✓		✓	✓	✓	✓				✓	✓		✓		✓	✓		✓		✓	✓
- Number of GSE types included	1	7	1	19	12	6	3	1	1	1	6	16		4	1	2	7	1	11	1	5	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 (per vehicle)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓		✓	✓			✓	✓	✓		✓
- Energy consumption of vehicles								✓		✓		✓		✓	✓			✓	✓	✓		✓
Considers eGSE								✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓
- Mixed fleets (electric and fossil fueled)										✓	✓	✓	✓							✓		✓
- Determines energy consumption								✓		✓	✓	✓	✓	✓		✓		✓		✓	✓	✓
- Charging (scheduling)								✓		✓	✓	✓	✓	✓		✓	✓	✓		✓	✓	
Determines number of vehicles						✓		✓				✓								✓		✓
Number of vehicles as an input	✓	✓	✓	✓	✓		✓		✓	✓	✓		✓	✓	✓	✓	✓	✓	✓			

[a] (icon): optimization of operations, (icon): energy management, (icon): operational costs, (icon): environmental impact.

study for sustainable aircraft refueling vehicles. The model results provide insights in future fleet mix and charging requirements to achieve carbon emission goals. Adeoye (2025) conducted a life cycle assessment (LCA) to compare the environmental impact of diesel, biodiesel, and electric GSE. The study shows that eGSE has the lowest direct emissions, but its overall environmental benefit depends on the electricity grid mix.

2.5. Scientific contribution

An overview of the relevant 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" (icon), "energy management" (icon), "operational costs" (icon), or "environmental impact" (icon). Based on literature research and expert interviews, several key components for modeling GSE operations at airports can be defined (see Table 1). These are further detailed in Section 3. The literature research shows that most studies focus on only one or a few GSE types and none incorporate all components deemed essential by the literature. The model will primarily focus on simulating and optimizing eGSE operations and their associated energy consumption. Although charging is not explicitly modeled, the energy consumption and depletion of vehicles are tracked, providing insight into the charging requirements. This enables a post-hoc analysis to assess whether opportunity charging could suffice or whether additional vehicles would be needed to maintain fleet capacity. In general, this research contributes to the field by:

- Considering all possible GSE types individually. All types of GSE can be added, by adjusting the parameters and tasks accordingly.
- Modeling the GSE turnaround operations including task allocation, travel times, service time windows, service times (with individual times for multiple vehicles per service) and the energy consumption of the vehicles.
- Determining the required number of vehicles and their energy demand. To this extent, field data from electric water trucks is used for verification, which has not yet been done in previous research.

Including the above elements results in a contribution as shown in the last column of Table 1. Given that 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 computational complexity of the model.

3. Background of (e)GSE operations

Each type of GSE has distinct properties, activities, and duty cycles. Based on ACRP reports (National Academies of Sciences, Engineering, and Medicine, 2012, 2015), GSE can be categorized by use case: (1.) ground power/air conditioning, (2.) aircraft movement, (3.) aircraft servicing, (4.) passenger (un)loading, and (5.) baggage/cargo handling. GSE operations depend on several variables that can vary considerably across airports, affecting the type, quantity, and service time of GSE. A distinction can be made between (1.) operational characteristics, (2.) aircraft characteristics, and (3.) airport infrastructure (ICAO, 2020). Operational procedures dictate the types and numbers of GSE services required, while aircraft characteristics influence stand allocation and handling procedures. Airport infrastructure, including the type and location of aircraft stands, can affect GSE numbers and operations, especially if stands are designated for specific aircraft types (e.g., cargo or passenger aircraft).

The electrification of GSE comes with the benefits of zero exhaust emissions, reduced maintenance, and higher energy efficiency, but also poses challenges, such as high initial costs, limited operational range, and charging infrastructure requirements (Adeoye, 2025).

The consumption of and the way in which smaller GSE is used makes that they typically consume less energy and can operate for a full day on a single charge. If needed, opportunity charging is feasible (according to expert interviews in Timmermans (2023)). Larger GSE, however, must be charged during operational hours due to limitations in battery capacity and the limited space and weight that can be spent on batteries. These vehicles therefore have a greater downtime than their diesel equivalents (according to expert interviews in Timmermans (2023)). While this study assumes that vehicles start with a full battery, this depends on local airport operations. Many airports, such as Amsterdam Airport Schiphol, are subject to night curfews as part of noise abatement strategies, limiting aircraft and GSE activity at night (Ashford et al., 2013), which supports the feasibility of overnight charging.

It has become apparent that there are many differences between the GSE types required for servicing aircraft at an airport. To maximize the model's applicability, it will incorporate vehicle-specific parameters and distinguish between vehicles with logistical loads (e.g., water and catering trucks) and those without.

4. Problem formulation

The problem at hand will be described as a Task Scheduling Problem (TSP). As noted by Bunte and Kliewer (2009), an optimal schedule minimizes fleet size and/or operational costs. These elements are at the heart of the problem. MILP is a powerful tool for planning and control problems (Earl and D'Andrea, 2005). In literature, it is widely applied to solve TSPs and VRPTWs (Kuhn and Loth, 2009; Wang et al., 2021; Bao et al., 2023) due to its strong modeling capabilities and the availability of good solvers. Therefore, the problem at hand will also be solved using MILP.

The model includes (1.) parking tasks, (2.) flight tasks, and (3.) logistics tasks. Two parking tasks are defined per location: one covering the full day from which a vehicle can depart, and one fixed at the end of the day to allow return. Flight tasks are derived from the flight schedule and the turnaround tables of the aircraft types. Each flight task i has an earliest (ET_i) and latest (LT_i) execution time, defining its time window. The task time (TT_i), with $TT_i \leq LT_i - ET_i$, follows from the turnaround table as well. The demand (DEM_i) and energy consumption (EC_i) depend on both aircraft and GSE type. A single flight may generate multiple flight tasks, based on the required number of vehicles and ground time. Since flight tasks are tied to aircraft stands, it is possible that there are several flight tasks with the same location if (1.) the flight schedule contains multiple flights with the same aircraft stand and/or (2.) multiple vehicles (of the same type) are required to service one flight. Logistics tasks support refilling or emptying vehicle compartments and are only relevant for GSE types with a logistical function. When placed before flight tasks, they enable vehicles to refill (e.g., catering, water) or empty (e.g., lavatory service, waste) their compartments as needed. This ensures that vehicles can meet service requirements without exceeding their capacity or operating with insufficient load.

4.1. Rolling horizon approach

To reduce the computation, a rolling horizon is employed, as similarly used by Kuhn and Loth (2009) for GSE scheduling. Algorithm 1 explains how it is applied in the context of this research. Let CT denote the current time and Π the set of unassigned flight tasks, with A representing the complete set of flight tasks. In 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, assigning vehicles $k \in K$ to tasks $i \in F$. Assigned tasks with start times $s_i \leq CT + t_{update}$ are added to Ω, where $t_{update} \leq t_{forward}$. These tasks are fixed, removed from Π, and the task list is updated. The current time is increased with t_{update}, and the 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 vehicles $k \in K$ and tasks $i \in F$
  $\Omega \leftarrow \{i \in F : s_i \leq CT + t_{update}\}$
  Assign: all tasks in Ω
  $\Pi \leftarrow \Pi \setminus \Omega$
  Update: overall task list together with vehicle states and SOC
  $CT \leftarrow CT + t_{update}$

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 the current task	$i \in T$
j	Index for the next task	$j \in T$
k	Index for the 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	$\mathbb{N}_0^+$
FN_i	Flight number associated with 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	$\mathbb{N}_0^+$

4.2. Mathematical model

The notations used in this paper are shown in Table 2. A distinction is made between numerical and modeling sets. Modeling sets may include subscripts indicating subsets: S (start tasks), I (intermediate tasks), and E (end tasks). For example, $P_S \subset P$ includes parking tasks designated as start tasks. If no subscript is indicated, the entire set is implied (e.g., $P_{SIE} = P$). After each optimization in the rolling horizon, modeling sets P, F, L, K_{unused}, K_{used}, and $K_{depleted}$ are updated, along with parameters RT_k, ST_k, SL_k, EP_k, and LOC_i.

The objective function consists of five components (obj. 1–5): (1.) the number of vehicles used, (2.) the distance traveled by all vehicles (in km), (3.) the number of visits to logistics tasks, (4.) the sum of flight task start times and (5.) the total waiting time of vehicles at logistics tasks. Components 1 and 2 are used for operational scenarios, while components 3, 4 and 5 are used to help the MILP's solver converge to a solution. Depending on the goal of the optimization, weights λ_1 to λ_5 can be altered to define the contribution of each term, with λ_3 to λ_5 kept small to avoid biasing the primary objectives.

$$\min \lambda_1 \underbrace{\left(\sum_{k\in K} z_k\right)}_{\text{obj. 1}} + \lambda_2 \underbrace{\left(\sum_{i\in T}\sum_{j\in T} \frac{D_{ij}}{1000} x_{ij}\right)}_{\text{obj. 2}} + \lambda_3 \underbrace{\left(\sum_{i\in F} s_i\right)}_{\text{obj. 3}} + \lambda_4 \underbrace{\left(\sum_{i\in T\setminus L}\sum_{j\in L} x_{ij}\right)}_{\text{obj. 4}} + \lambda_5 \underbrace{\left(\sum_{i\in L} w_i\right)}_{\text{obj. 5}}$$

4.2.1. Generic constraints

Constraints (1) and (2) link x_{ij} and y_i. Constraint (3) ensures that $z_k = 1$ if vehicle k is used for a task in F. Constraint (4) enforces flow conservation for tasks in T_I. Constraints (5) and (6) ensure that task j can only be visited once and task i can only be left once, respectively. Constraint (7) ensures that vehicles do not drive from task i to task i. Constraints (8) and (9) prevent vehicles from entering start tasks or exiting end tasks, respectively. Constraint (10) prevents direct travel from a start to an end task.

$$y_j = \sum_{i\in T} x_{ij} \qquad \forall j \in T_{IE} \tag{1}$$

$$y_i = \sum_{j\in T} x_{ij} \qquad \forall i \in T_S \tag{2}$$

$$z_k \geq y_i \qquad \forall k \in K,\ i = ST_k \tag{3}$$

$$\sum_{i\in T} x_{ih} = \sum_{j\in T} x_{hj} \qquad \forall h \in T_I \tag{4}$$

$$\sum_{i\in T} x_{ij} \leq 1 \qquad \forall j \in T \tag{5}$$

$$\sum_{j\in T} x_{ij} \leq 1 \qquad \forall i \in T \tag{6}$$

$$x_{ii} = 0 \qquad \forall i \in T \tag{7}$$

$$x_{ij} = 0 \qquad \forall i \in T,\ j \in T_S \tag{8}$$

$$x_{ij} = 0 \qquad \forall i \in T_E,\ j \in T \tag{9}$$

$$x_{ij} = 0 \qquad \forall i \in T_S,\ j \in T_E \tag{10}$$

Constraints (11) and (12) ensure that visiting a task cannot start before ET_i or after LT_i, respectively. Constraints (13) and (14) ensure that a vehicle cannot start with task j before arriving at task j. Constraint (15) ensures that a vehicle does not start the servicing of task j before it arrives there (when traveling from starting task ST_k).

$$s_i \geq ET_i \qquad \forall i \in T \tag{11}$$

$$s_i \leq LT_i \qquad \forall i \in T \tag{12}$$

$$s_j \geq s_i + TT_i + w_i + \frac{D_{ij}}{V} - M\left(1 - x_{ij}\right) \qquad \forall i,j \in T,\ i \neq j \tag{13}$$

$$s_j \leq s_i + TT_i + w_i + \frac{D_{ij}}{V} + M\left(1 - x_{ij}\right) \qquad \forall i,j \in T,\ i \neq j \tag{14}$$

$$s_j \geq \left(RT_k + \frac{D_{ij}}{V}\right) x_{ij} \qquad \forall j \in T,\ i = ST_k,\ k = LOC_i \tag{15}$$

Constraint (16) enforces sequential vehicle reuse, allowing a vehicle to be used only if all previously used vehicles are reactivated. Constraint (17) allows a parking task to be assigned only if the vehicle that was parked at the location in the previous run is active in the current run. Constraint (18) prohibits the use of depleted vehicles.

$$z_k \leq z_l \qquad \forall k \in K_{unused},\ l \in K_{used} \tag{16}$$

$$y_i \leq y_h \qquad \forall k \in K,\ i = EP_k,\ h = ST_k \tag{17}$$

$$z_k = 0 \qquad \forall k \in K_{depleted} \tag{18}$$

4.2.2. Flight task constraints

Constraint (19) ensures that all flight tasks are performed. Constraints (20) and (21) ensure that performing task i cannot start before ET_i or end after LT_i, respectively.

$$y_i = 1 \qquad \forall i \in F \tag{19}$$

$$s_i \geq ET_i \qquad \forall i \in F \tag{20}$$

$$s_i \leq LT_i - TT_i \qquad \forall i \in F \tag{21}$$

4.2.3. Logistic task constraints

Constraints (22) and (23) 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 (24) requires vehicles to depart the logistics task fully loaded. Constraints (25) and (26) set the initial load of vehicle k at the starting task to SL_k.

$$q_j \leq q_i - DEM_j + Q\left(1 - x_{ij}\right) \qquad \forall i \in T,\ j \in T \setminus L,\ i \neq j \tag{22}$$

$$q_j \geq q_i - DEM_j - Q\left(1 - x_{ij}\right) \qquad \forall i \in T,\ j \in T \setminus L,\ i \neq j \tag{23}$$

$$q_i \geq C - Q\left(1 - x_{ij}\right) \qquad \forall i \in L,\ j \in T \setminus L \tag{24}$$

$$q_i \geq SL_k \qquad \forall i \in T_s,\ k = LOC_i \tag{25}$$

$$q_i \leq SL_k \qquad \forall i \in T_s,\ k = LOC_i \tag{26}$$

Constraint (27) enforces a waiting time of R minutes per added load unit at a logistics task. Constraint (28) ensures vehicle departure from a logistics task before LT_i.

$$w_j \geq R\left(q_j - q_i\right) - M\left(1 - x_{ij}\right) \qquad \forall i \in T,\ j \in L \tag{27}$$

$$s_i + w_i \leq LT_i \qquad \forall i \in L \tag{28}$$

Constraint (29) ensures that vehicle loads cannot exceed the vehicle's capacity. Constraint (30) prohibits direct travel between logistics tasks. Constraint (31) only permits travel from a logistics task to its associated flight task. Constraint (32) prohibits travel from a logistics task to a parking task.

$$q_i \leq C \qquad \forall i \in T \tag{29}$$

$$x_{ij} = 0 \qquad \forall i,j \in L \tag{30}$$

$$x_{ij} = 0 \qquad \forall i \in L,\ j \in F,\ FN_i \neq FN_j \tag{31}$$

$$x_{ij} = 0 \qquad \forall i \in L,\ j \in P \tag{32}$$

5. Complexity reduction

The NP-complete nature of many scheduling problems, and MILP-models in general, precludes their solution 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 branch-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 following constraints, though mathematically redundant, accelerate convergence by imposing upper bounds on continuous variables and tightening the feasible region.

$$s_i \le ET_i + M\left(1 - y_i\right) \qquad \forall i \in P_S \tag{33}$$

$$s_i \le ET_i + M\left(1 - y_i\right) \qquad \forall i \in P_E \tag{34}$$

Constraint (33) forces a vehicle to start at ET at the start P task that is used. Constraint (34) forces a vehicle to arrive at its end P task at ET.

5.2. Model density

Although the formulation is mathematically sound, the model contains many binary variables that could never be part of a feasible solution under the model's constraints, resulting in a highly sparse model.

Following an approach similar to the chain decomposition of Hooker and Natraj (1995), a large subset of (i,j)-pairs can be eliminated in advance by filtering based on feasibility conditions. This preprocessing step does not affect the set of potentially optimal solutions, as only infeasible decisions are removed. The reduction of (i,j)-pairs can go up to > 85%. Let T denote the set of tasks, and define $G_0 = \{\ (i,j)\ \mid i,j \in T\ \}$ as the set of all task pairs. Then, the steps to reduce the (i,j)-pairs are:

$$G_1 = G_0 \setminus \{\ (i,j)\ \mid i,j \in G_0, i = j\ \}$$

$$G_2 = G_1 \setminus \{\ (i,j) \mid i,j \in G_1, i \in L, j \in F, FN_i \neq FN_j \}$$

$$G_3 = G_2 \setminus \{\ (i,j)\ \mid i,j \in G_2, j \in T_S\ \}$$

$$G_4 = G_3 \setminus \{\ (i,j)\ \mid i,j \in G_3, i \in T_E\ \}$$

$$G_5 = G_4 \setminus \{\ (i,j)\ \mid i,j \in G_4, i,j \in L\ \}$$

$$G_6 = G_5 \setminus \{\ (i,j)\ \mid i,j \in G_5, i \in L, j \in P\ \}$$

$$G_7 = G_6 \setminus \{\ (i,j)\ \mid i,j \in G_6, i \in T_S, j \in T_E\ \}$$

$$G_8 = G_7 \setminus \left\{\ (i,j) \,\middle|\, i,j \in G_7, ET_i + TT_i + \frac{D_{ij}}{V} > LT_j - TT_j\ \right\}$$

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 generated only for vehicles with logistics tasks, with $L = \emptyset$ otherwise. Similarly, the decision variable q_i and associated "logistics task constraints" are included only when necessary. This approach decreases computational load in two ways: (1.) because the optimization problem contains less variables, it can be solved faster, and (2.) because there are fewer constraints and variables, the model can be set up faster.

5.3. Model symmetry

Degeneracy in MILP problems arises when multiple distinct assignments of binary variables yield the same optimal objective value, leading to symmetric feasible solutions. 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

$$C(|K|, N) = \binom{|K|}{N} = \frac{|K|!}{N!\,(|K| - N)!}$$

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

$$\binom{|K|}{N} N! = \frac{|K|!}{N!\,(|K| - N)!} N! = \frac{|K|!}{(|K| - N)!}$$

equivalent solutions.

To break the first type of symmetry, a constraint, based on the work of Adulyasak et al. (2014), can be used: constraint (35) ensures that vehicle k can only be used if vehicle $k-1$ is used.

$$z_k \le z_{k-1} \qquad \forall k \in K_{unused} \setminus \min\left(K_{unused}\right) \tag{35}$$

To address the second symmetry issue, a hierarchical constraint inspired by Darvish et al. (2020) can be used: constraint (36) 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 $k-1$.

$$x_{ij} \le \sum_{j'=\min T_B}^{j-1} x_{i'j'}$$
$$\forall j \in T_B,\ \ k \in K_{unused} \setminus \min\left(K_{unused}\right),$$
$$k' \in K_{unused},\ \ k' = k - 1,\ \ i = ST_k,\ \ i' = ST_{k'} \tag{36}$$

Both constraints are valid inequalities that strengthen the model formulation. To prevent suboptimality, these symmetry-breaking constraints can only be used if all vehicles in the fleet are homogeneous and start at the same location. The constraints are therefore only applied in the model if this is possible without excluding optimal solutions.

6. Case study

To validate the model, a case study is conducted on KLM Royal Dutch Airlines' GSE fleet at Amsterdam Airport Schiphol (AAS). The MILP model is implemented in Python and solved using Gurobi. This paper includes the validation for a GSE type without a logistics function (belt loader) and for a GSE type with a logistics function (water truck). We refer to Timmermans (2023) for the complete model verification and 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 is based on the IATA Busy Day definition (IATA, 2022). Based on this definition, July 13 2023 was selected as the IATA Busy Day. After filtering for airlines serviced by KLM Ground Services, the schedule contained 735 Air Traffic Movements (ATMs), as shown in Fig. 1. The ATMs were paired to create turnarounds.
- 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, based on ground time.
- Distances: the aircraft stands, parking locations, and logistics locations were grouped into 35 clusters, based on internal KLM documentation. It also includes the distances between the location clusters, and based on this, the shortest distance between all combinations of the location clusters was calculated. For trips within a cluster, the average distance between all locations within the cluster was used. The mean of the distances is $\mu = 1.23$ km and the standard deviation is $\sigma = 0.82$ km.

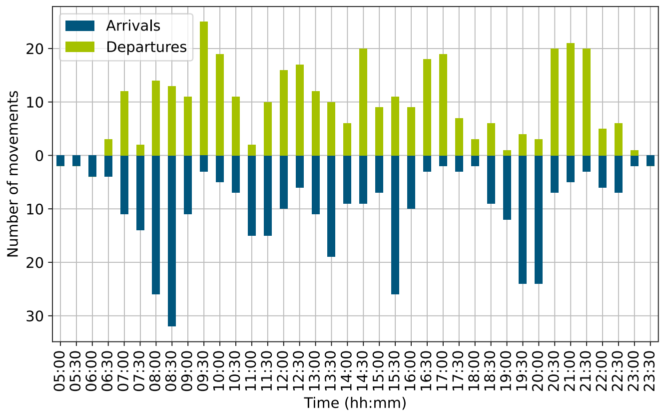

Fig. 1. An overview of the air traffic movement quantities that were serviced by KLM Ground Services at AAS on July 13, 2023.

Table 3
Vehicle parameters used in the case study.

(a) Parameters for the MILP model.		
Parameter	Belt loader	Water truck
V	15 km/h	15 km/h
C		3300 L
R		3.7 L/s
(b) Parameters for calculating the energy consumption.		
Parameter	Belt loader	Water truck
Battery capacity	33.6 kWh	70.0 kWh
Energy demand for driving	0.59 kWh/km	1.00 kWh/km
Power demand for task	1.0 kW	0.7 kW

- 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 the belt loaders (driving and performing tasks) and the water trucks (performing tasks). Field data has been collected for the energy consumption of the driving of the water trucks (see Section 6.2). An average speed of 15 km/h was assumed for the driving speed. An overview of the vehicle parameters used for the case study is provided in Table 3.

6.2. Field measurements of water trucks

To assess the energy consumption of KLM Ground Services' electric water trucks, field measurements were conducted. Various operators registered the mileage, battery percentages, charging events, and aircraft servicing tasks during their shifts. Based on this data, the distance driven and the amount of kWh used were calculated. A fixed energy value per aircraft servicing was subtracted from the total consumption to isolate driving-related use, allowing calculation of consumption per kilometer. Fig. 2 provides insight into the driven kilometers, energy consumption, and consumption per kilometer. Based on the 23 measurements, an average consumption of 1.04 kWh/km was found, with an IQR between 0.91 and 1.13 kWh/km.

6.3. Normalization of the objective function

The objective function as discussed in Section 4 was first normalized for each GSE type to ensure that the analysis is performed across the relevant range of objective values. Only the first two sub-objectives, minimizing the number of vehicles used and distance driven, were

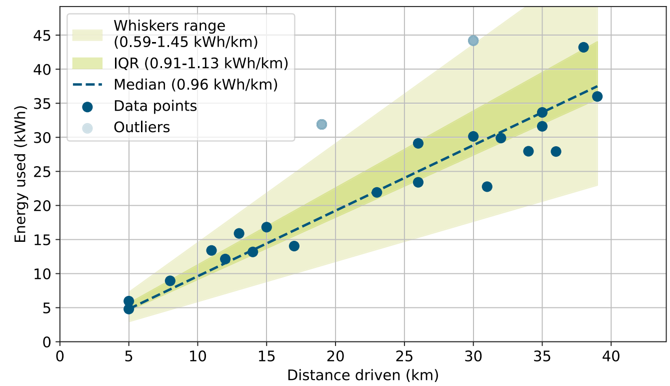

Fig. 2. Plot showing the relationship between distance driven and energy used, based on the field measurements for the water trucks.

considered. The model was executed twice, with weighting factors $(\lambda_1, \lambda_2) = (500, 0.001)$ and $(\lambda_1, \lambda_2) = (0.001, 500)$, respectively.

Because the optimization utilizes a rolling horizon, multiple separate optimizations are solved to find the overall solution, each yielding distinct objective values. For the normalization, the average sub-objective values over all runs with $|F| > 0$ were computed. The difference between these averages from the two weighting schemes defined the correction parameters α and β. Next to this, the first two sub-objectives were scaled by a factor of 10^4 to dominate the objective function and maintain values in the order of 10^4, facilitating optimal performance in Gurobi. Based on these adjustments, the following objective function was obtained:

$$\min \lambda_1 \cdot \frac{10^4}{\alpha} \cdot \underbrace{\left(\sum_{k\in K} z_k\right)}_{\text{obj. 1}} + \lambda_2 \cdot \frac{10^4}{\beta} \cdot \underbrace{\left(\sum_{i\in T}\sum_{j\in T} \frac{D_{ij}}{1000} x_{ij}\right)}_{\text{obj. 2}}$$
$$+ \lambda_3 \underbrace{\left(\sum_{i\in F} s_i\right)}_{\text{obj. 3}} + \lambda_4 \underbrace{\left(\sum_{i\in T\setminus L}\sum_{j\in L} x_{ij}\right)}_{\text{obj. 4}} + \lambda_5 \underbrace{\left(\sum_{i\in L} w_i\right)}_{\text{obj. 5}}$$

6.4. Pareto fronts

To gain insight into the trade-off between the number of vehicles and the distances traveled, Pareto fronts have been created for the belt loaders and water trucks. Two metrics are considered: the total number of vehicles used in a day and the maximum number of vehicles required within a 30 min time window. To this end, the weighting factors λ_1 and λ_2 are varied from 0.001 to 1.00, in increments, subject to $\lambda_1 + \lambda_2 = 1.00$.

6.4.1. Belt loaders

Fig. 3 shows the Pareto front for the belt loaders. Some noticeable solutions are:

- Solution 6 with $(\lambda_1, \lambda_2) = (0.70, 0.30)$: This solution utilizes 37 vehicles, both during peak time and throughout the day, achieving the lowest total distance (48.773 km) with this minimized number of vehicles.
- 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 are used during the day.
- Solution 18 with $(\lambda_1, \lambda_2) = (0.001, 0.999)$: 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.

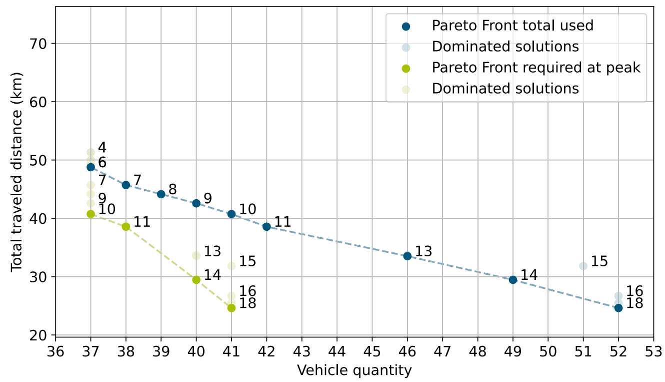

Fig. 3. Two Pareto-fronts for the sensitivity analysis of the multi-objective optimization for the belt loader operations. The numbered labels next to the data points correspond to a combination of λ_1 and λ_2.

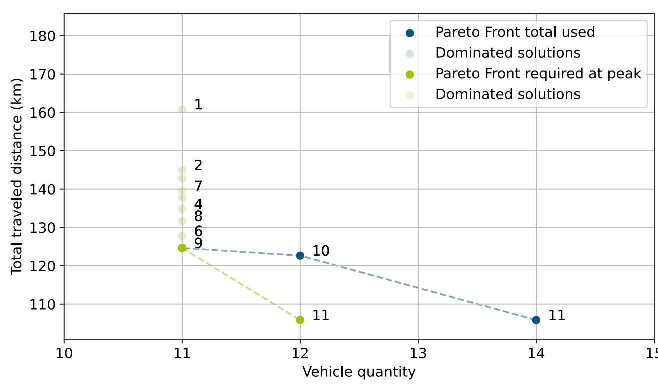

Fig. 4. Two Pareto-fronts for the sensitivity analysis of the multi-objective optimization for the water truck operations. The numbered labels next to the data points correspond to a combination of λ_1 and λ_2.

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 presents solutions outside the Pareto front. Analysis of the results has shown that these solutions exhibit inefficiencies attributed to the rolling horizon approach. In these cases, vehicle assignments that are optimal in one optimization step prove suboptimal in subsequent stages.

6.4.2. Water trucks

Fig. 4 shows the Pareto front for the water trucks. Some noticeable solutions are:

- Solution 9 with $(\lambda_1, \lambda_2) = (0.20, 0.80)$: This solution utilizes 11 vehicles, both during peak time and throughout the day, achieving the lowest total distance (124.640 km) with this minimized number of vehicles.
- Solution 11 with $(\lambda_1, \lambda_2) = (0.001, 0.999)$: This is the solution with the lowest total traveled distance (105.841 km). This requires a total of 14 vehicles. During the peak, 12 of these vehicles are used.

It can be deduced that a minimization of the total traveled distance in this case does not result in a significant increase in the number of vehicles required. Putting a new vehicle into use comes with a relatively high initial "fixed" distance because the water trucks first have to go to the logistics location to collect water.

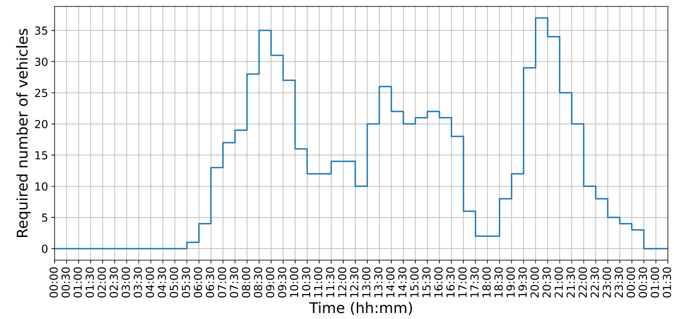

Fig. 5. The required number of belt loaders per 30 min.

6.5. Model validation

To validate the model, one Pareto-optimal solution for the belt loaders and water trucks is selected for further analysis. The solution minimizing the total number of vehicles and the corresponding traveled distance is chosen, as it is the most financially advantageous. Where possible, model outcomes are compared with operational data from KLM Royal Dutch Airlines.

6.5.1. Belt loaders

Solution 6 $(\lambda_1, \lambda_2) = (0.70, 0.30)$ from Fig. 3 is selected for the model validation. Fig. 5 illustrates the number of vehicles required throughout the day. The average utilization rate is approximately 21%, calculated as the ratio of time spent on tasks (including driving) to the total available time (24 h). The figure also indicates that charging opportunities exist between peak periods.

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 this is independent of the driving. If desired, the 29 kWh can be reduced by using more vehicles, as can be seen in Fig. 3. None of the belt loaders had a depleted battery at the end of the day.

The data available at KLM shows that the number of belt loaders, as determined by the model, is slightly too high, but within the correct 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. 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. When the belt loaders were initially purchased, their batteries were sized to last a full day without charging. However, battery degradation over time has caused some batteries to now have a State of Health (SOH) below the 100% assumed in the model.

6.5.2. Water trucks

Solution 9 $(\lambda_1, \lambda_2) = (0.20, 0.80)$ from Fig. 4 is selected for the model validation. Fig. 6 illustrates the number of vehicles required throughout the day. The average utilization rate is approximately 26%, calculated as the ratio of time spent on tasks (including driving) to the total available time (24 h). The figure shows that there are limited daytime charging opportunities, necessitating reliance on opportunity charging during operations and overnight charging.

A total of 155 kWh was used to execute the task schedule. Of this, 30 kWh (19%) was used to perform the tasks on the aircraft stands, i.e., operating the pump, and 125 kWh (81%) was used for driving a total distance of 124.640 km. This makes clear that most of the energy can be optimized, by minimizing the total traveled distance. None of the water trucks had a depleted battery at the end of the day.

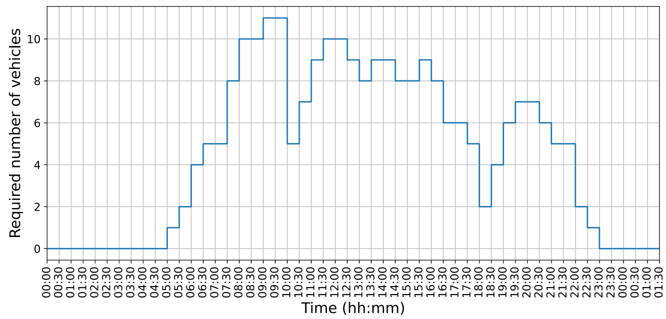

Fig. 6. The required number of water trucks per 30 min.

Table 4
Sensitivity analysis for required task times.

(a) Solution results for belt loaders.

Change	Required vehicles (total) [–]	Required vehicles (peak) [–]	Total traveled distance [km]
−20%	28	28	55.410
−10%	32	32	48.724
−5%	35	35	47.619
0%	37	37	48.773

(b) Solution results for water trucks.

Change	Required vehicles (total) [–]	Required vehicles (peak) [–]	Total traveled distance [km]
−20%	10	10	122.088
−10%	10	10	122.849
−5%	11	11	121.706
0%	11	11	124.640

The data available at KLM shows that the number of water trucks as determined by the model is correct. However, not all water trucks at KLM are currently electric. There is a significant difference between the distance driven in reality and in the model. In reality, the vehicles drive much more because they cannot remain stationary near the aircraft stand after completing a task, as assumed in the model. This is because the operators are tied to their vehicles during their shift and can also be assigned to other tasks, for which they do not need a water truck and must first return to the depot. Due to the higher number of kilometers driven, it is necessary to recharge the vehicles in between tasks, i.e., opportunity charging is used. Additionally, conversations with KLM reveal that aircraft sometimes receive multi-stretch servicing. This means that aircraft are serviced for several flights at once, so they do not require service after every flight. As a result, there are fewer tasks, making it possible to operate with fewer vehicles. The higher number of kilometers and the lower number of tasks compared to the model result in approximately the same number of required vehicles in this case.

6.6. Sensitivity analysis

To examine the robustness of the model, two sensitivity analyses are conducted. The first varies the required task times (TT_i) by decreasing them by 5%, 10%, and 20%. Increases are not considered as these would exceed the tight time windows. The second adjusted the vehicle travel speeds (V) by both increasing and decreasing them by 5%, 10%, and 20%.

6.6.1. Required time for task

As shown in Table 4, when the required task time of the vehicles is gradually decreased by up to 20%, the required number of belt loaders also decreases. The same can be observed for the water trucks, but to a lesser extent because fewer vehicles are needed here. It implies that measures to reduce the task time could reduce the required number of vehicles. The total traveled distance fluctuates for both vehicle types, likely because fewer vehicles must cover greater distances to service the same number of flights, obscuring a clear trend.

Table 5
Sensitivity analysis for travel speed of vehicles.

(a) Solution results for belt loaders.

Change	Required vehicles (total) [–]	Required vehicles (peak) [–]	Total traveled distance [km]
−20%	38	37	48.558
−10%	38	37	46.342
−5%	37	37	48.575
0%	37	37	48.773
5%	38	37	44.754
10%	37	37	48.086
20%	37	37	46.462

(b) Solution results for water trucks.

Change	Required vehicles (total) [–]	Required vehicles (peak) [–]	Total traveled distance [km]
−20%	12	12	120.697
−10%	11	11	124.794
−5%	12	12	125.939
0%	11	11	124.640
5%	11	11	125.980
10%	11	11	122.090
20%	11	11	125.072

6.6.2. Travel speed of vehicles

As shown in Table 5, when the travel speed of the vehicles is gradually adjusted from −20% to +20%, the required number of vehicles and the total traveled distance fluctuate slightly and irregularly. This indicates that the travel speed has little effect on the solution, primarily because task durations dominate driving times. Consequently, measures to improve traffic flow or adjust speed limits are unlikely to significantly affect fleet size or daily distances, nor would increased congestion.

7. Discussion

Section 3 confirmed that GSE types vary significantly in their characteristics. Consequently, the model developed in this study differentiates between different GSE types to enable broader applicability. Furthermore, a distinction was made between vehicles with logistical loads and those without. This approach addresses a gap identified in the literature, where few studies encompass the full range of GSE types. The model results effectively estimate vehicle requirements, energy consumption, and optimization potential. However, validation revealed that, despite differentiating between GSE types, operational differences among these types still impact the outcomes. Notably, the assumption that the GSE remains near the aircraft stands between tasks had a significant impact on the validation results for water trucks, but this factor was less influential for belt loaders, which are generally parked close to the aircraft stands. 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 high-level planning. However, it should be noted that the rolling horizon approach does not guarantee overall optimality in the solutions. By incorporating essential operational components identified through literature and interviews, the model supports decision-making at an operational level across multiple GSE types more effectively than comparable models, which often rely on greater simplifications.

An important assumption in this study is that the vehicles are primarily used during the day and can be fully recharged overnight. This assumption aligns with the operational context of Amsterdam Airport Schiphol, which is subject to a strict night curfew. Consequently, it implies that vehicles in the case study start each day with a fully charged battery. However, it is recognized that this condition may not be generalizable to airports with continuous 24-h operations and no curfew restrictions. In such contexts, the model outcomes would differ, requiring opportunity charging during operational hours or an increased fleet size to maintain the fleet capacity. While charging is not explicitly modeled, the model tracks battery depletion over time, allowing charging requirements to be estimated indirectly. This enables an indication of whether opportunity charging could be sufficient or whether more vehicles would be needed. Nevertheless, for applications requiring more detailed operational planning, such as charger placement, scheduling of charging events, or power infrastructure design, explicit modeling of the charging process would likely be necessary. These limitations do not affect the core functioning of the model but should be considered in future adaptations to different operational contexts.

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 largely depends on the type of GSE and the way in which it is used. 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.

The model results show that both smaller and larger types of eGSE can be used for a complete day on a full battery charge. A condition for this is that the vehicles are not needed at night, which allows them to get fully charged again. This is the case at many airports due to nighttime curfews. The way in which the vehicles are used is also very important in this regard. Parking a vehicle near the aircraft stand between tasks results in significantly fewer kilometers driven, lower energy consumption, and thus longer usability before the vehicle needs to be recharged. Based on the model validation, it turns out that certain GSE types can indeed run out before the end of the day, based on the way they are used. To maintain the fleet capacity of these GSE types, it is necessary to either (1.) use more of these vehicles, (2.) charge the vehicles during operational hours, (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 operational hours does not necessarily result in maintained fleet capacity, as this depends on the availability of charging opportunities. This is related to the available charging capacity and how tasks are distributed throughout the day. Using the developed model, it is possible to determine how many additional vehicles are needed when opportunity charging is not feasible. For opportunity charging itself, an estimate can be made based on the model results, 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.

Further research could also explore balancing the availability of renewable energy sources with different types of energy storage and charging methods. The work of van Oosterom et al. (2023) provides a useful example of a method for routing vehicles and scheduling them for either flight tasks or battery recharging, which could serve as a foundation for this research.

CRediT authorship contribution statement

Koen Timmermans: Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Formal analysis, Conceptualization. **Paul Roling:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization. **Gautham Ram Chandra Mouli:** Writing – review & editing, Validation, Supervision, Methodology. **Bilge Atasoy:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Koen Timmermans reports financial support was provided by KLM Royal Dutch Airlines. Koen Timmermans reports a relationship with KLM Royal Dutch Airlines that includes: employment.

Other authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Adeoye, I., 2025. Life cycle assessment of diesel, biodiesel, and electric ground support equipment in airports: A comparative environmental impact study. http://dx.doi.org/10.2139/ssrn.5130847.

Adulyasak, Y., Cordeau, J.-F., Jans, R., 2014. Formulations and branch-and-cut algorithms for multivehicle production and inventory routing problems. INFORMS J. Comput. 26 (1), 103–120. http://dx.doi.org/10.1287/ijoc.2013.0550.

Ahmadi, S., Akgunduz, A., 2023. Airport operations with electric-powered towing alternatives under stochastic conditions. J. Air Transp. Manag. 109, 102392. http://dx.doi.org/10.1016/j.jairtraman.2023.102392.

Akande, M., 2025. Carbon footprint analysis of airport ground operations: Evaluating the transition from diesel to biodiesel and electric power sources. http://dx.doi.org/10.2139/ssrn.5138504.

Alonso Tabares, D., Mora-Camino, F., Drouin, A., 2021. A multi-time scale management structure for airport ground handling automation. J. Air Transp. Manag. 90, 101959. http://dx.doi.org/10.1016/j.jairtraman.2020.101959.

Alruwaili, M., Cipcigan, L., 2022. Airport electrified ground support equipment for providing ancillary services to the grid. Electr. Power Syst. Res. 211, 108242. http://dx.doi.org/10.1016/j.epsr.2022.108242.

Ashford, N.J., Stanton, H.M., Moore, C.A., AAE, P.C., Beasley, J.R., 2013. Airport Operations. McGraw-Hill Education.

Bahman, N., 2023. Airport sustainability through life cycle assessments: A systematic literature review. Sustain. Dev. 31 (3), 1268–1277. http://dx.doi.org/10.1002/sd.2498.

Bao, D.-W., Zhou, J.-Y., Zhang, Z.-Q., Chen, Z., Kang, D., 2023. Mixed fleet scheduling method for airport ground service vehicles under the trend of electrification. J. Air Transp. Manag. 108, 102379. http://dx.doi.org/10.1016/j.jairtraman.2023.102379.

Benosa, G., Zhu, S., Kinnon, M.M., Dabdub, D., 2018. Air quality impacts of implementing emission reduction strategies at southern California airports. Atmos. Environ. 185, 121–127. http://dx.doi.org/10.1016/j.atmosenv.2018.04.048.

Bosma, T., 2022. Design of an Airport Service Infrastructure for Sustainable Refueling of Aircraft: Model Development for the Quantification of CO2e Emissions, Total Cost of Ownership and Grid Load Effects of Electrified Refueler Fleets at Future Airports (Master's thesis). Delft University of Technology.

Brelje, B.J., Martins, J.R., 2019. Electric, hybrid, and turboelectric fixed-wing aircraft: A review of concepts, models, and design approaches. Prog. Aerosp. Sci. 104, 1–19. http://dx.doi.org/10.1016/j.paerosci.2018.06.004.

Bunte, S., Kliewer, N., 2009. An overview on vehicle scheduling models. Public Transp. 1 (4), 299–317. http://dx.doi.org/10.1007/s12469-010-0018-5.

Charlatte, 2017. Technical datasheet CBL2000E.

Darvish, M., Coelho, L.C., Jans, R., 2020. Comparison of Symmetry Breaking and Input Ordering Techniques for Routing Problems. CIRRELT.

Earl, M., D'Andrea, R., 2005. Iterative MILP methods for vehicle-control problems. IEEE Trans. Robot. 21 (6), 1158–1167. http://dx.doi.org/10.1109/tro.2005.853499.

European Commission, 2021. Reducing emissions from aviation.

European Union Aviation Safety Agency, 2022. European Aviation Environmental Report 2022. Publications Office.

Francfort, J., Morrow, K., Hochard, D., 2007. Cost Benefit Analysis Modeling Tool for Electric vs. ICE Airport Ground Support Equipment - Development and Results. Technical Report, Office of Scientific and Technical Information (OSTI), http://dx.doi.org/10.2172/911917.

Gamrath, G., Berthold, T., Salvagnin, D., 2020. An exploratory computational analysis of dual degeneracy in mixed-integer programming. EURO J. Comput. Optim. 8 (3–4), 241–261. http://dx.doi.org/10.1007/s13675-020-00130-z.

Gök, Y.S., Padrón, S., Tomasella, M., Guimarans, D., Ozturk, C., 2022. Constraint-based robust planning and scheduling of airport apron operations through simheuristics. Ann. Oper. Res. 320 (2), 795–830. http://dx.doi.org/10.1007/s10479-022-04547-0.

Gulan, K., Cotilla-Sanchez, E., Cao, Y., 2019. Charging analysis of ground support vehicles in an electrified airport. In: 2019 IEEE Transportation Electrification Conference and Expo. ITEC, IEEE, pp. 1–6. http://dx.doi.org/10.1109/itec.2019.8790550.

Hájnik, A., Harantová, V., Kalašová, A., 2021. Use of electromobility and autonomous vehicles at airports in europe and worldwide. Transp. Res. Procedia 55, 71–78. http://dx.doi.org/10.1016/j.trpro.2021.06.008.

Hooker, J.N., Natraj, N.R., 1995. Solving a general routing and scheduling problem by chain decomposition and tabu search. Transp. Sci. 29 (1), 30–44. http://dx.doi.org/10.1287/trsc.29.1.30.

IATA, 2022. Airport development reference manual. 12 ed..

ICAO, 2020. Airport air quality manual (Doc 9889).

Kirca, M.C., McGordon, A., Dinh, T.Q., 2020. Multi-input multi-output model of airport infrastructure for reducing CO2 emissions. In: 2020 IEEE Vehicle Power and Propulsion Conference. VPPC, IEEE, pp. 1–6. http://dx.doi.org/10.1109/vppc49601.2020.9330949.

Kuhn, K., Loth, S., 2009. Airport service vehicle scheduling. In: ATM Seminar 2009.

Miller, I.A., Rutledge, A., 2025. Airport electrification: Funding, microgrids, and sustainability. J. Aviat. Technol. Eng. 14 (1), http://dx.doi.org/10.7771/2159-6670.1314.

National Academies of Sciences, Engineering, and Medicine, 2012. Airport Ground Support Equipment (GSE): Emission Reduction Strategies, Inventory, and Tutorial. Transportation Research Board, http://dx.doi.org/10.17226/22681.

National Academies of Sciences, Engineering, and Medicine, 2015. Improving Ground Support Equipment Operational Data for Airport Emissions Modeling. Transportation Research Board, http://dx.doi.org/10.17226/22084.

Orientitan Ground Support Equipment, 2019. Datasheet HD-WS40 aircraft water truck.

Padrón, S., Guimarans, D., 2019. An improved method for scheduling aircraft ground handling operations from a global perspective. Asia-Pac. J. Oper. Res. 36 (04), 1950020. http://dx.doi.org/10.1142/s0217595919500209.

Padrón, S., Guimarans, D., Ramos, J.J., Fitouri-Trabelsi, S., 2016. A bi-objective approach for scheduling ground-handling vehicles in airports. Comput. Oper. Res. 71, 34–53. http://dx.doi.org/10.1016/j.cor.2015.12.010.

Roslöf, J., Harjunkoski, I., Westerlund, T., Isaksson, J., 2002. Solving a large-scale industrial scheduling problem using MILP combined with a heuristic procedure. European J. Oper. Res. 138 (1), 29–42. http://dx.doi.org/10.1016/s0377-2217(01)00140-0.

Saggar, S., Tomasella, M., Cattaneo, G., Matta, A., 2021. Enhanced operational management of airport ground support equipment for better aircraft turnaround performance. In: 2021 Winter Simulation Conference. WSC, IEEE, pp. 1–12. http://dx.doi.org/10.1109/wsc52266.2021.9715320.

Salihu, A.L., Lloyd, S.M., Akgunduz, A., 2021. Electrification of airport taxiway operations: A simulation framework for analyzing congestion and cost. Transp. Res. Part D: Transp. Environ. 97, 102962. http://dx.doi.org/10.1016/j.trd.2021.102962.

Sari, M., Wan Mohamed, W.M., Jalil, S.A., 2022. The optimization using electric ground support equipment in aviation industry. Int. J. Energy Econ. Policy 12 (1), 401–406. http://dx.doi.org/10.32479/ijeep.11711.

Sherali, H.D., Smith, J.C., 2001. Improving discrete model representations via symmetry considerations. Manag. Sci. 47 (10), 1396–1407. http://dx.doi.org/10.1287/mnsc.47.10.1396.10265.

Soares, L., Wang, H., 2021. Economic feasibility analysis of charging infrastructure for electric ground fleet in airports. Transp. Res. Rec.: J. Transp. Res. Board 2675 (12), 1–12. http://dx.doi.org/10.1177/03611981211033859.

Sznajderman, L., Coppa, M., Martiarena, J.F., Olariaga, O.D., 2022. Quantification model of airport ground support equipment emissions. Aviation 26 (4), 195–208. http://dx.doi.org/10.3846/aviation.2022.17967.

Timmermans, K., 2023. Electric Ground Support Equipment at Airports: The Impact of Implementing eGSE on the Capacity and Demand of GSE Fleets (Master's thesis). Delft University of Technology.

TLD, 2023. Datasheet TLD nbl-e electrical conveyor belt.

Van Baaren, E., Roling, P.C., 2019. Design of a zero emission aircraft towing system. In: AIAA Aviation 2019 Forum. American Institute of Aeronautics and Astronautics, http://dx.doi.org/10.2514/6.2019-2932.

van Oosterom, S., Mitici, M., Hoekstra, J., 2023. Dispatching a fleet of electric towing vehicles for aircraft taxiing with conflict avoidance and efficient battery charging. Transp. Res. Part C: Emerg. Technol. 147, 103995. http://dx.doi.org/10.1016/j.trc.2022.103995.

Vestergaard, 2023. Datasheet vestergaard e.

Wang, S., Che, Y., Zhao, H., Lim, A., 2021. Accurate tracking, collision detection, and optimal scheduling of airport ground support equipment. IEEE Internet Things J. 8 (1), 572–584. http://dx.doi.org/10.1109/jiot.2020.3004874.

Xiang, Y., Cai, H., Liu, J., Zhang, X., 2021. Techno-economic design of energy systems for airport electrification: A hydrogen-solar-storage integrated microgrid solution. Appl. Energy 283, 116374. http://dx.doi.org/10.1016/j.apenergy.2020.116374.

Yim, S.H., Stettler, M.E., Barrett, S.R., 2013. Air quality and public health impacts of UK airports. Part II: Impacts and policy assessment. Atmos. Environ. 67, 184–192. http://dx.doi.org/10.1016/j.atmosenv.2012.10.017.

Zhang, J., Chong, X., Wei, Y., Bi, Z., Yu, Q., 2022. Optimization of apron support vehicle operation scheduling based on multi-layer coding genetic algorithm. Appl. Sci. 12 (10), 5279. http://dx.doi.org/10.3390/app12105279.

Zoutendijk, M., Mitici, M., Hoekstra, J., 2023. An investigation of operational management solutions and challenges for electric taxiing of aircraft. Res. Transp. Bus. & Manag. 49, 101019. http://dx.doi.org/10.1016/j.rtbm.2023.101019.