Journal of Air Transport Management 119 (2024) 102633

Contents lists available at ScienceDirect

Journal of Air Transport Management

journal homepage: www.elsevier.com/locate/jairtraman

Modular vehicles can reduce greenhouse gas emissions for departure flight baggage transportation

Xiaowei Shi [a], Zhiwei Chen [b,c,*], Xiaopeng Li [d,**], Xiaobo Qu [e]

[a] Department of Civil and Environmental Engineering, University of Wisconsin-Milwaukee, Milwaukee, WI, USA
[b] Department of Civil, Architectural, & Environmental Engineering, Drexel University, Philadelphia, PA, USA
[c] Department of Electrical & Computer Engineering, Drexel University, Philadelphia, PA, USA
[d] Department of Civil & Environmental Engineering, University of Wisconsin - Madison, Wisconsin WI, USA
[e] School of Vehicle and Mobility, Tsinghua University, Beijing, China

ARTICLE INFO

Keywords:
Aviation
Greenhouse gas emission
Modular vehicle
Baggage
Scheduling

ABSTRACT

Rapid and on-time baggage transportation plays a crucial role in ensuring customer satisfaction and is an important source of greenhouse gas (GHG) emissions in the aviation sector. Modular Vehicle (MV) is an emerging transportation technology that allows vehicles to adjust their capacity flexibly by assembling or disassembling identical detachable units. This innovative technology offers a new perspective to decarbonize the aviation sector, as it holds promise for reducing GHG emissions in flight baggage transportation. To investigate this possibility, this study proposes an MV operation paradigm and a corresponding "greenest" MV scheduling problem that aims to minimize MV-relevant GHG emissions while transporting baggage from the terminal to the aircraft without delay. To solve the problem efficiently, a fast construction-merging heuristic is proposed based on the theoretical properties of the problem. A series of case studies at the Tampa International Airport were conducted to evaluate the performance of the proposed MV operation and the construction-merging heuristic. The results indicate that the proposed MV operation effectively reduces GHG emissions, and the heuristic solves near-optimal solutions to the investigated problem much faster than Gurobi, a state-of-the-art commercial solver for integer programs, without much loss of the optimality of the solutions. Results from this study provide important managerial and operational insights into decarbonizing baggage transportation for airport operators.

1. Introduction

Aviation plays a key role in global climate change, accounting for approximately 3.5% of global warming effects induced by greenhouse gas (GHG) emissions (Lee et al., 2021). This number is expected to increase given the continuous growth of the aviation market worldwide (Peeters et al., 2016). In response, major aviation stakeholders across the world have set goals to reduce carbon dioxide (CO_2, a type of GHG) emissions by 50% by 2050, compared to 2005 levels. The Aviation Emissions and Air Quality Handbook (Federal Aviation Administration, 2022) has identified the primary sources of GHG emissions within the aviation sector as follows: aircraft operations (73%), ground support equipment and access vehicle operations (20%), auxiliary power units (3%), and stationary sources (4%). Efforts have thus been made to decarbonize the aviation sector in various areas such as technology, operations, infrastructure, and alternative fuels (ATAG, 2011). These efforts, however, have not paid the same attention to flight baggage transportation, an important component of ground support equipment and access vehicle operations and an important source of aviation GHG emissions.

Flight baggage transportation generally involves two steps. Take baggage for departure flights shown in Fig. 1 as an example. Baggage is transported, first, from check-in areas or connecting flights to unloading areas within the terminal and, second, from the terminal to the aircraft. To streamline flight baggage transportation, many airports have introduced Baggage Handling Systems (BHS) (Huang et al., 2016). In this streamlined process, baggage checked in or transferred from a connecting flight first undergoes X-ray security screening. Following security clearance, it proceeds to the main sorter, where its destination is identified and assigned. The baggage is then directed to the assigned

* Corresponding author. Department of Civil, Architectural, & Environmental Engineering, Drexel University, Philadelphia, PA, USA.
** Corresponding author.
E-mail addresses: zc392@drexel.edu (Z. Chen), xli2485@wisc.edu (X. Li).

https://doi.org/10.1016/j.jairtraman.2024.102633
Received 8 March 2023; Received in revised form 20 May 2024; Accepted 17 June 2024
Available online 24 June 2024

destination, which could be either an unloading or buffer area. Baggage in the buffer area must wait for reassignment to an unloading area. Baggage in the unloading area is collected, loaded onto human-driven carts, and transported to the aircraft by ground crews.

While the BHS enhances many aspects of flight baggage transportation, it is still a significant source of GHG emissions. Extensive efforts in BHS design, such as baggage tracking (Zhang et al., 2008), system control (Zeinaly and Wang H, 2019), system simulation (Lin et al., 2015), baggage routing (Johnstone et al., 2010), and baggage assignment (e.g., Huang et al., 2016, 2018) have allowed BHS to alleviate the burdens on the airport ground crews and to increase customer satisfaction. Despite recent efforts to develop low-carbon solutions to flight baggage transportation (Fontela et al., 2007; Helber et al., 2018; Lodewijks et al., 2021), the BHS remains a major energy consumer at airports, with belt conveyors using over 55% of the energy consumed by a BHS (Vogel, 2010; van Enter, 2018). In addition, human-driven transportation carts powered by combustion engines also use large quantities of fuel during their frequent travel between unloading areas and aircraft (Howards, 2001; Forbes, 2019). Consequently, the GHG emissions from flight baggage transportation (proportional to fuel consumption (Lodewijks et al., 2021), including the movement of baggage from check-in areas or connecting flights to unloading areas via the BHS, and from the terminal to the aircraft via human-driven transportation carts, remain substantial. This also results in high operating costs. Baggage transportation at the Tampa International Airport (TPA), for example, produced a cost of $1,127,153 in 2019 (Tampa International Airport, 2019).

The emerging modular vehicle (MV) technologies potentially offer a unique solution to further reducing GHG emissions in flight baggage transportation, which has not yet been investigated in the literature. Currently, baggage transportation between terminals and aircraft is undertaken mainly by human-driven carts with little or no optimization. As a result, the transportation capacity provided by the dispatched carts is not well aligned with the baggage transportation demand, resulting in an increase in the energy to transport the same amount of baggage and the associated GHG emissions. MVs are a new vehicle technology that allows small pods to flexibly assemble and disassemble into vehicles of different lengths (and thus capacity) during operations. This new technology is being developed and tested in several countries. For example, the Connected and Autonomous Transportation System Lab at the University of South Florida used robot cars to demonstrate the concatenation and detachment processes of MVs in 2017, as shown in Fig. 2 (Li, 2022). NEXT, a for-profit corporation, demonstrated full-scale MVs in Dubai in 2018, as shown in Fig. 3 (NEXT, 2018). These pilot programs have inspired a few proof-of-concept studies that proposed innovative operational solutions for multiple transportation systems using MV technologies (Dai et al., 2020; Guo et al., 2018; Hassold and Ceder, 2014; Mo et al., 2019; Scherr et al., 2018, 2019; Zhang et al., 2020). Systems that have been investigated include transit shuttles (Chen et al., 2019, 2020), shared-use transit corridors (Shi et al., 2020), and transit corridors (Shi and Li, 2021; Chen and Li., 2021). These studies have demonstrated that MVs have the potential to decrease the system operating costs (mainly energy costs). Given that GHG emissions are related to energy consumption (all else being equal, the higher the energy consumption, the higher the GHG emissions if traditional energy sources such as fuel are used), MVs have great potential to reduce GHG emissions for flight baggage transportation as well. However, existing studies on MVs have only investigated transit systems with one-to-one (i.e., shuttle) and unidirectional many-to-many (i.e., corridor) demand structures. A flight baggage transportation system is essentially a one-to-many distribution system where vehicles travel between terminals and aircraft repeatedly to transport baggage, and the baggage arrival of each aircraft is independent [Please refer to Sections 5 and 6 in Daganzo (1996) for more details regarding the differences between system structures.]. It is not known whether the findings from one-to-one and unidirectional many-to-many transit systems are transferable to one-to-many flight baggage transportation systems or not.

To answer the above question, models and algorithms are needed to schedule MVs that transport baggage from unloading areas to aircraft (named MV scheduling for the convenience of the illustration). The one-to-many demand structure of flight baggage transportation systems makes models and algorithms in existing MV studies not applicable. Although not specifically focused on GHG emissions, several studies have investigated the way to optimally schedule ground support vehicles at airports (Liu et al., 2022; Zhu et al., 2022). However, none of these studies have considered the flexible capacity operations enabled by MVs. Additionally, one may wonder whether models and algorithms for the vehicle routing problem with time windows (VRPTM) – a highly relevant problem that investigates the dispatch of vehicles to serve passengers/goods with predefined travel origins, destinations, and time windows using a limited vehicle fleet – are applicable to MV scheduling for flight baggage transportation or not. Studies on VRPTM have considered a fleet of heterogeneous vehicles categorized based on their size (capacity), with a fixed or unlimited number of vehicles available of each size. These studies viewed vehicles of different sizes as separate groups of vehicles operating independently. With MV technologies, however, vehicles of different sizes are transferable by adding or removing modular carts (MC). The number of vehicles of each size, unlike that in the VRPTM, is a variable depending on decisions to add or remove MCs during operations. For example, assume there are three MCs in stock, and the maximum number of MCs in one vehicle is three. There will be three possible fleet compositions: three 1-MC vehicles (i.e.,

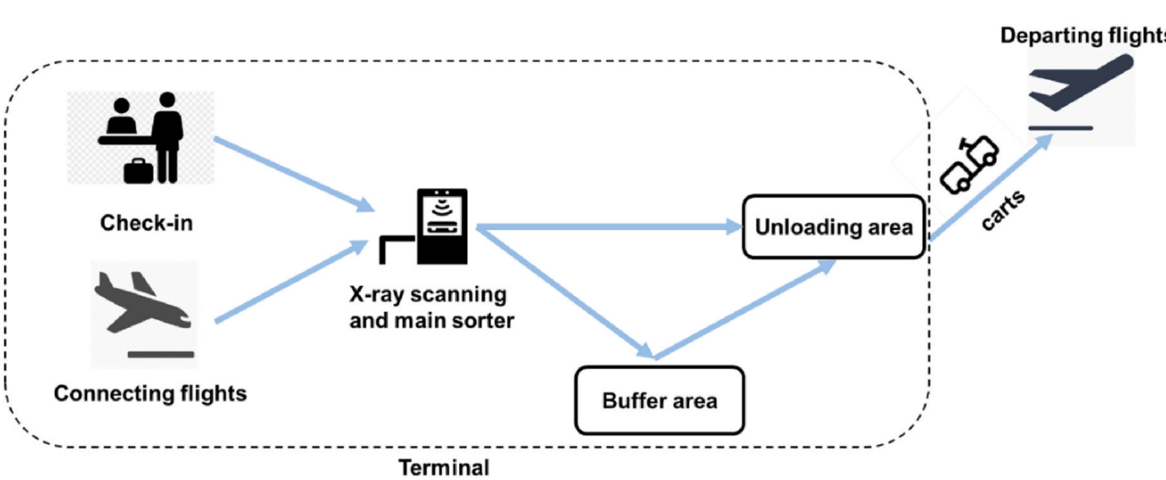

Fig. 1. Streamlined baggage transportation process at airports (created by the authors).

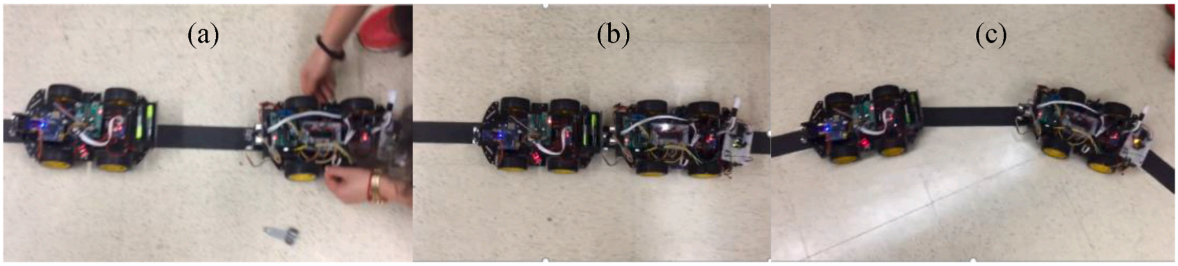

Fig. 2. Scaled MV experiments conducted in the U.S. (Li, 2022).

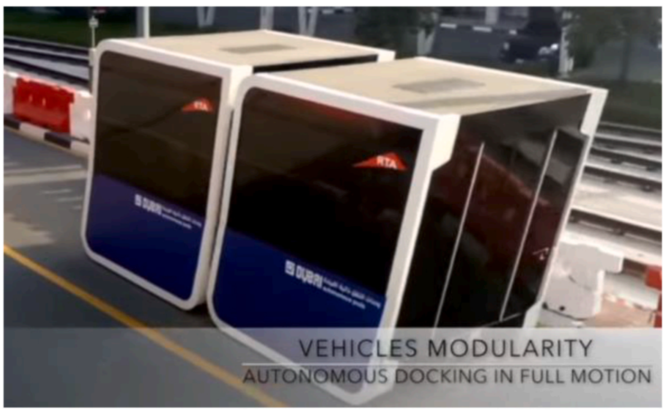

Fig. 3. Full-scale MVs demonstrated by NEXT in Dubai (NEXT, 2018).

$\{1,1,1\}$), one 1-MC vehicle and one 2-MC vehicle (i.e., $\{1,2\}$), and one 3-MC vehicle (i.e., $\{3\}$), illustrated in Fig. 4. During operations, the fleet can morph into any of these three compositions with different numbers of vehicles of each size to fit the demand and reduce operating costs and GHG emissions. Consequently, the modular operation concept alters the problem structure and makes MV scheduling fundamentally different from the VRPTM. Particularly, without knowing the number of each type of vehicle, the original linear constraints that bound the number of each type of vehicle in the heterogenous VRPTW are invalid. Methodological efforts are needed to address this challenge.

This study aims to formulate, analyze, and evaluate the possibility of using MVs to reduce GHG emissions for airport baggage transportation, using departure flights as an example. We first propose a MV operation paradigm for departure flight baggage transportation. With MV technologies, a baggage transportation vehicle can be composed of a varying number of identical MCs, such that vehicle capacity is flexibly varied by concatenating or detaching MCs as demand changes. Specifically, vehicles are dispatched using a higher number of MCs and a higher frequency during periods with intensive demand (peak hours). Grouping individual MCs into long vehicles reduces energy consumption and thus GHG emissions by splitting fixed energy costs among MCs, which is the well-known concept of the economy of scales in transportation and logistics. This can also be treated as an extreme case of vehicle platooning where the physical gap between MCs reaches zero. Thus, energy saving due to platooning, such as a decrease in the aerodynamic drag, would also be achieved. In contrast, vehicles consisting of a smaller number of MCs can be dispatched during periods with relatively sparse demand using a relatively low frequency. This will also contribute to reducing GHG emissions as the energy that would have been wasted on moving empty or low-occupancy MCs will be saved. Because existing models and algorithms do not apply to the investigated problem, we propose an optimization model to generate the "greenest" dispatch schedule for the MV-based baggage transportation system, which aims to minimize the GHG emissions for airports while transporting baggage without delay. Due to the scale of this real-world problem, state-of-the-art commercial solvers, e.g., Gurobi, cannot solve the problem within several hours. Thus, a fast construction-merging heuristic is proposed, leveraging the theoretical properties of the feasible solution region. To evaluate the performance of the proposed MV operation (in reducing GHG emissions) and the heuristic algorithm (in solving the problem), numerical experiments were conducted with data from the TPA. Sensitivity analysis was conducted to provide managerial insights into the proposed design. Overall, the contributions of this paper to the literature are twofold.

(1) This study proposes an innovative MV operation paradigm for airport baggage transportation to assess the potential of using emerging MV technologies to reduce GHG emissions at airports. This is a new problem that has not been studied previously. A set of case studies at the TPA was conducted to evaluate the performance of the MV-based solutions. Results confirm that MVs can effectively reduce GHG emissions from departure flight baggage transportation under various demand and parameter settings.
(2) The airport MV scheduling problem is rigorously formulated into a mixed integer programming model. The fundamental difference between the proposed and existing models makes existing algorithms not applicable to the investigated problem. A parsimonious and efficient construction-merging heuristic algorithm is thus proposed. Compared with a state-of-the-art commercial solver, Gurobi, the construction-merging heuristic algorithm solves near-optimal solutions to the investigated problem much faster without much loss of the optimality of the solutions, which is promising to facilitate real-world implementations with limited computation resources and real-time response requirements.

This proof-of-concept study shows the potential of the emerging MV technologies as an effective solution to decarbonize flight baggage transportation. It also provides models and algorithms that airport designers and operators can adopt to derive green baggage transportation solutions based on the MV technologies in practice. Although this study focuses on the emerging MV technologies that are still being developed, the modular operation concept also applies to existing human-driven carts. The difference is that the ground crews must assemble and dissemble MCs manually to fit the baggage volume, possibly incurring additional operating costs and GHG emissions. Still, the findings from

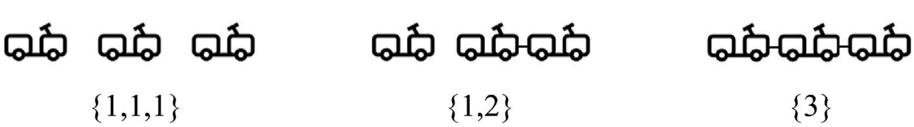

Fig. 4. A toy example of transferrable fleet compositions.

this study offer a theoretical upper bound to the potential of modular operations in reducing GHG emissions for flight baggage transportation.

The rest of this paper is organized as follows. Section 2 presents the MV-based departure flight baggage transportation system design and the MV scheduling problem in this system. Section 3 proposes a construction-merging heuristic algorithm to efficiently solve the proposed problem. To evaluate the proposed design, Section 4 discusses a series of case studies with baggage demand data from the TPA. Section 5 concludes the paper and identifies directions for future research.

2. Problem statement and model formulation

This section presents the proposed MV-based departure flight baggage transportation operation, the associated green MV scheduling problem, and the optimization model. We first offer a formal description of the system and the notation that is necessary for the model formulation. Next, the optimization model proposed to find the greenest MV dispatch plan is presented, followed by a formal analysis of the complexity of the model. Key notation used throughout the paper is summarized in Table 1.

2.1. Problem statement

Consider an airport with a set of aircraft denoted by $\mathscr{I} := \{1, 2, \cdots, I\}$. The aircraft is stopped at the aprons for loading passenger baggage and planned to leave the aprons sequentially during a studied time horizon $[0, \mathbb{T}]$. For the convenience of the modeling, the time horizon $[0, \mathbb{T}]$ is divided into discrete time intervals denoted by $\mathscr{T} := \{1, 2, \cdots, T\}$ with an equal length of $\theta := \mathbb{T}/T$. In practice, the modeler needs to choose a proper value of T to determine the length of each time duration. In the following analysis, index $t \in \mathscr{T}$ denotes the beginning of time interval t. The scheduled departure time for each aircraft is denoted by $d_i, \forall i \in \mathscr{I}$, which means that all baggage must be loaded into aircraft i before time d_i. We index the aircraft in a way that their scheduled departure time increases as the index increases; that is, $\forall i < j \in \mathscr{I}$, we have $d_i < d_j$. During the studied time horizon, baggage is checked in and transported to the unloading area. The number of check-in baggage pieces for aircraft i at time t, denoted as $p_{it}, \forall i \in \mathscr{I}, t \in \mathscr{T}$ (also known as baggage arrival rates), is predicted based on the historical data.

Baggage pieces at the unloading area are picked up and transported to the aircraft by a set of vehicles. The travel time between the terminal and aircraft i is denoted by $e_i, \forall i \in \mathscr{I}$. The handling time for baggage destined for aircraft i is denoted by $h_i, \forall i \in \mathscr{I}$. As handling time is not the focus of this paper, to simplify the problem structure, we assume that the handling time for each aircraft is fixed. Also, it is assumed that e_i and h_i are the integral multiple of θ. Different from existing fixed-capacity vehicles, this paper proposes an operation paradigm using MVs. Each MV is composed of several identical MCs. The capacity for one MC is c, and the initial number of MCs available at the terminal is V. The number of MCs in each MV can be changed flexibly based on the number of baggage pieces to be transported from the terminal. Without loss of generality, the maximum number of MCs in one MV is set to L, and, thus, the set of possible MC numbers in one MV is denoted as $\mathscr{L} := \{1, 2, \cdots, L\}$, indexed by $l \in \mathscr{L}$. A MV consisting of l MCs is called an l-MC MV. To estimate the GHG emissions of MVs, we adopt a simple model where the GHG emissions linearly increase with the energy consumption (Fontaras et al., 2017). Note that although there are sophisticated models for GHG emission modeling in the literature (e.g., Ben Cheikh et al., 2021; Chunyu et al., 2021), which may provide a more accurate estimation of GHG emissions, these models are nonlinear and affect the tractability of the problem. The focus of this study is to obtain first-order information in terms of how MVs will affect GHG emissions. A linear model, despite its simplicity, suffices to capture the fundamental relationship between emissions and vehicle length (capacity). We thus leave the investigation of more sophisticated models for emission modeling for future work. Then, according to previous studies on MVs, the fuel cost of MVs exhibits an economics of scales, i.e., the average fuel consumed by each MC decreases as the number of MCs in a MV increases (Chen et al., 2019; Sun and Yin, 2019). With this, the energy consumption and thus the associated GHG emissions can be represented as a concave function with respect to the number of MCs in a MV. Let f_{il} be the GHG emission of a l-MC MV destined for aircraft i. Then, it can be formulated as $f_{il} := C_i^F + C^V(lc)^\alpha, \forall i \in \mathscr{I}, l \in \mathscr{L}$, where C_i^F is the fixed GHG emissions determined by the travel time, C^V is the variable GHG emissions dependent on the MV size, and $\alpha \le 1$ is a power index quantifying the extent of the economies of scale.

The objective of this study is to find the "greenest" dispatch schedule for the MVs. Specifically, we aim to determine an optimal plan that dispatches the MVs to transport the baggage from the unloading area to each aircraft before the aircraft leaves such that the overall GHG emissions is minimized. This is called the green MV scheduling problem in this paper. Decisions to make in this problem include MV dispatch time, MV size (i.e., number of MCs in dispatched MVs), destined aircraft, and number of baggage pieces transported by each MV. These decisions can be mathematically expressed as the following decision variables:

y_{ilt}: represents whether an l-MC MV is dispatched to transport the baggage to aircraft i at time t, which equals 1 if yes and 0 otherwise.

v_t: number of MCs remaining at the unloading area at time t.

b_{it}: number of baggage assigned at time t destined for aircraft i.

Fig. 5 provides a toy example to facilitate the understanding of the investigated MV scheduling problem. It involves two aircraft in a time horizon divided into nine time intervals (i.e., $I = 2$, $T = 9$). The latest check-in time for aircraft 1 and 2 are, respectively, times 5 and 8 (i.e., $g_1 = 5$, $g_2 = 8$), and the aircraft is scheduled to depart at times 6 and 9 (i.e., $d_1 = 6$, $d_2 = 9$), respectively. For aircraft 1, the check-in baggage arrives in time intervals 1–4, and the number of check-in baggage pieces for these intervals is $\{1, 2, 1, 1\}$, respectively. For aircraft 2, the check-in baggage arrives in time intervals 4–7, and the number of check-in baggage pieces for these intervals is $\{1, 2, 3, 4\}$, respectively. The initial number of MCs available at the terminal is 5 (i.e., $V = 5$). The maximum MCs allowed in one MV is set to 3, and the capacity of one MC is 5 pieces of baggage (i.e., $L = 3$, $c = 5$). We assume that there is no handling time for baggage, and the travel time is set to a large number so no vehicle circulation occurs in this toy example. Note that these assumptions only apply to this toy example and not the general model formulation in Section 2.3. The GHG emissions for operating a MV with l

Table 1
Notation.

Parameters	
$[0, \mathbb{T}]$	Studied time horizon.
$\mathscr{I}$	Set of aircraft, $\mathscr{I} := \{1, 2, \cdots, I\}$.
$\mathscr{T}$	Set of studied time interval, $\mathscr{T} := \{1, 2, \cdots, T\}$.
$\mathscr{L}$	Set of MCs in one MV, $\mathscr{L} := \{1, 2, \cdots, L\}$.
θ	Length of a time interval. $\theta = \mathbb{T}/T$.
d_i	Scheduled departure time for aircraft $i, \forall i \in \mathscr{I}$.
g_i	Latest check-in time for aircraft $i, \forall i \in \mathscr{I}$.
p_{it}	Number of check-in baggage for aircraft i at time interval t, $\forall i \in \mathscr{I}, t \in \mathscr{T}$.
c	Capacity for one MC.
L	Maximum number of MCs in one MV.
e_i	Travel time between the terminal and aircraft i, $\forall i \in \mathscr{I}$.
h_i	Handling time for baggage destined for aircraft i, $\forall i \in \mathscr{I}$.
f_{il}	GHG emissions operating a MV with l MCs to aircraft i, $\forall i \in \mathscr{I}, l \in \mathscr{L}$.
V	The initial number of MCs available at the terminal.
a_i	Arrival time of the first baggage piece for aircraft $i, \forall i \in \mathscr{I}$.
$\mathbb{E}_i$	Effective dispatch period for aircraft $i, \forall i \in \mathscr{I}$.
s_{it}	Number of baggage pieces waiting to be transported to aircraft i till time interval t, $\forall i \in \mathscr{I}, t \in \mathscr{T}$.
Decision variables	
y_{ilt}	$= 1$, if a MV with l MCs destined for aircraft i is dispatched at time t. $= 0$, otherwise. $\forall i \in \mathscr{I}, l \in \mathscr{L}, t \in \mathscr{T}$
v_t	Number of MCs available at terminal at time $t, \forall t \in \mathscr{T}$.
b_{it}	Number of baggage assigned at time t destined for aircraft i, $\forall i \in \mathscr{I}, t \in \mathscr{T}$.

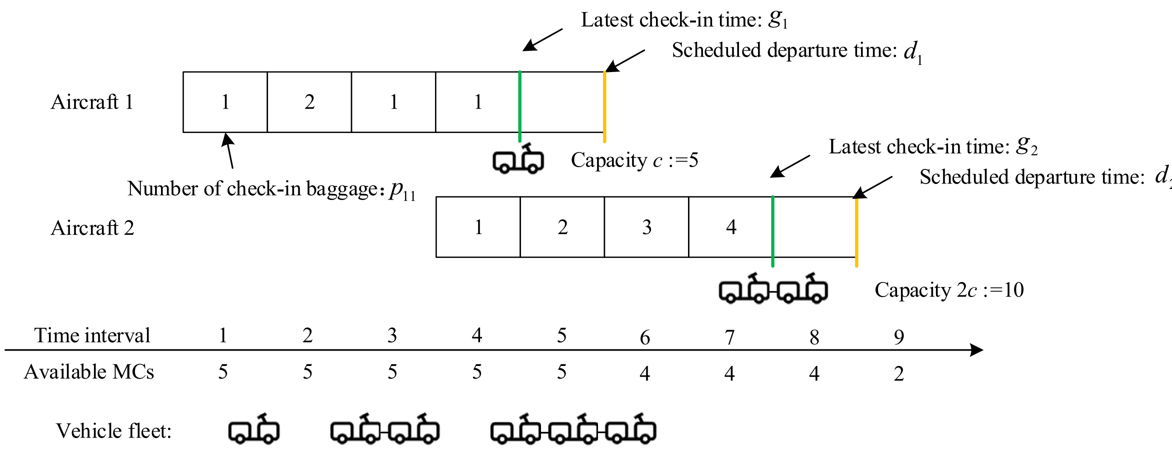

Fig. 5. Toy example for MV scheduling problem.

MCs is simply set to l regardless of the travel distance. With these settings, the green MV scheduling problem aims to minimize the GHG emissions of the two MVs while transporting all baggage to the corresponding aircraft before the aircraft leaves. An optimal solution is shown in Fig. 5. Specifically, one MV with one MC is dispatched to aircraft 1 at time 5, accommodating 5 pieces of baggage (i.e., $y_{115} = 1; b_{15} = 5$). A second MV with two MCs is dispatched to aircraft 2 at time 8, accommodating 10 pieces of baggage (i.e., $y_{228} = 1, b_{28} = 10$). The number of MCs remaining at the unloading area is $v_t := \{5,5,5,5,5,4,4,4,2\}$. At the end of the time horizon, all baggage is transported to the corresponding aircraft without delay. This optimal plan produces total GHG emissions of 3 (i.e., number of dispatched MCs). The number of MCs available at the terminal over the studied time horizon is shown in Fig. 5.

2.2. Model formulation

We formulate the problem of finding the greenest MV dispatch plan into an optimization model. The model introduces two sets of constraints that describe the general operational requirements of airport departure baggage transportation, and an objective function to reflect the goal of our design. As discussed in Section 2.1, the following three assumptions are made to formulate the problem without loss of generality.

Assumption 1. The number of check-in baggage pieces (i.e., p_{it}), which is a parameter of the model, are known (e.g., predicted based on historical data, generated by simulation software). Thus, this study is solving a planning problem.

Assumption 2. In real-world applications, handling time (i.e., h_i) would vary depending on how many baggage pieces are loaded or unloaded. However, as handling time is not the focus of our study, we have treated it as a constant for simplicity.

Assumption 3. An emission model where the GHG emissions are linearly increased with the energy consumption is adopted to capture the fundamental relationship between emissions and vehicle length (MV types).

2.2.1. Constraints on MV dispatch

The set of constraints related to MV dispatch is formulated as Constraints (1)–(5). Constraint (1) shows that the number of MCs dispatched must be less than or equal to the number of MCs available in the unloading area at the terminal. Constraint (2) indicates that, at most, one MV (across all types) can be dispatched for each aircraft in each time interval. Constraints (3) and (4) describe the MC circulation in the system. Specifically, Constraint (3) sets the number of MCs available in the unloading area at the beginning of the studied time horizon. Constraints (4) show that the number of MCs available at time $t+1$ equals the number of MCs available minus the number of MCs dispatched plus the number of MCs that return to the terminal at time t. Note that the circulation time for one MV between the terminal and aircraft i equals the round-trip travel time ($2e_i$) plus twice the handling time ($2h_i$), as the baggage pieces need to be loaded at the terminal and unloaded at the aircraft. Thus, the number of MCs that return to the terminal at time t equals the number of MCs dispatched at $t - 2e_i - 2h_i$ to all aircraft $i \in \mathscr{I}$. For the convenience of notation, we define $y_{ilt} = 0$ if $t \leq 0$. Constraint (5) defines variables y_{ilt}, indicating that the values of y_{ilt} can be only 1 or 0.

$$\sum_{i\in\mathscr{I},l\in\mathscr{L}} l\cdot y_{ilt} \leq v_t, \forall t \in \mathscr{T}, \tag{1}$$

$$\sum_{l\in\mathscr{L}} y_{ilt} \leq 1, \forall i \in \mathscr{I}, t \in \mathscr{T}, \tag{2}$$

$$v_1 = V, \tag{3}$$

$$v_{t+1} = v_t - \sum_{i\in\mathscr{I},l\in\mathscr{L}} l\cdot y_{ilt} + \sum_{i\in\mathscr{I},l\in\mathscr{L}} l\cdot y_{il(t-2e_i-2h_i)}, \forall t \in \{1,2,\cdots,T-1\}, \tag{4}$$

$$y_{ilt} \in \{0,1\}, \forall i \in \mathscr{I}, l \in \mathscr{L}, t \in \mathscr{T}, \tag{5}$$

2.2.2. Constraints on baggage movement

These constraints are imposed to describe the baggage movement between the unloading area and aircraft. Constraints (6) and (7) indicate that the number of baggage pieces transported to an aircraft during any time interval cannot exceed the number of baggage checked in. Constraint (8) is the capacity restriction, meaning that the number of baggage transported cannot be greater than the capacity of the MV dispatched. Constraint (9) is necessary to ensure that all the check-in baggage pieces are transported to the corresponding aircraft. That is, for each aircraft, the sum of the number of baggage transported to an aircraft over all time intervals should equal the total number of check-in baggage for that aircraft.

$$b_{i1} \leq p_{i1}, \forall i \in \mathscr{I}, \tag{6}$$

$$b_{it} \leq p_{it} + \sum_{t'=1}^{t-1} (p_{it'} - b_{it'}), \forall i \in \mathscr{I}, t \in \mathscr{T}\backslash\{1\}, \tag{7}$$

$$b_{it} \leq c\sum_{l\in\mathscr{L}} l\cdot y_{ilt}, \forall i \in \mathscr{I}, t \in \mathscr{T}, \tag{8}$$

$$\sum_{t'=1}^{d_i-e_i-2h_i} \boldsymbol{b}_{it'} = \sum_{t''=1}^{g_i} \boldsymbol{p}_{it''}, \forall \boldsymbol{i} \in \mathscr{I}, \tag{9}$$

2.2.3. Objective

The objective of the design is to minimize the overall GHG emissions of MVs across all aircraft, MV types, and time within the studied period while transporting baggage to the corresponding aircraft. This is mathematically formulated as Equation (10),

$$\min_{y_{ilt}, v_t, b_{it}} \sum_{i\in\mathscr{I}, l\in\mathscr{L}, t\in\mathscr{T}} f_{il} \cdot y_{ilt}. \tag{10}$$

2.3. Model complexity

Despite its rigorous formulation, model (1)–(10) is in fact a very complex problem. In this subsection, we formally analyze the complexity of the model. Specifically, we proved the NP-hardness of the investigated problem by showing that the classroom scheduling problem, known as NP-hard (Pinedo, 2008; Elffers, 2018), can be reduced to the investigated problem in a polynomial time.

Proposition 1. *Problem (1) – (10) is NP-hard.*

Proof. A generic classroom scheduling problem is stated as follows. Given a set of classes $\mathscr{I}$, indexed as $\boldsymbol{i} \in \mathscr{I}$, with the start time $\boldsymbol{s_i}$ and finish time $\boldsymbol{r_i}$, the problem is to determine whether these classes can be scheduled in $\boldsymbol{R}$ classrooms within a given time horizon $[\mathbf{0}, \mathbb{T}]$. We can transfer this problem instance into an equivalent instance of the investigated problem. In this equivalent instance, we set the capacity of one MC unit vehicle unit to a sufficiently large number such that the baggage demand for each aircraft can be transported with a 1-MC MV. Further, we set $\boldsymbol{d_i} = \boldsymbol{r_i}, \boldsymbol{g_i} = \boldsymbol{s_i}, \boldsymbol{f_i} = \mathbf{1}, \boldsymbol{e_i} = \mathbf{0}, \boldsymbol{h_i} = \mathbf{0}, \boldsymbol{V} = \boldsymbol{R}$. Then, a solution to the investigated problem instance also solves the classroom scheduling problem instance. That is, if there is a solution to problem (1) – (10), the answer to the generic classroom scheduling problem is yes; otherwise, the answer is no. Obviously, this transformation between the investigated problem and the classroom scheduling problem only takes a polynomial number of operations (or a polynomial time). This proves the NP-hardness of the model (1)–(10). □

3. Solution algorithm

The investigated green MV scheduling problem is formulated into a linear integer programming model. By using a state-of-the-art commercial solver, Gurobi, on a personal computer, it took as long as 2 h to solve model (1)–(10) to optimality for real-world large-scale problem instances (see Section 4 for numerical results). This long computational time may greatly restrict real-world applications of the proposed model. To circumvent this computational issue, we developed a fast construction-merging heuristic algorithm that can efficiently solve the green MV scheduling problem in a much shorter time. This section first presents the theoretical properties we adopt for the algorithm development, and then the proposed construction-merging heuristic is discussed.

3.1. Solution properties

This section analyzes the theoretical properties of the investigated problem. These properties will be used to develop the construction-merging heuristic in the following section. We first investigate the properties of a feasible solution. In a feasible dispatching solution, a MV must be dispatched between the latest check-in time (i.e., $\boldsymbol{g_i}$) and the latest dispatch time (i.e., $\boldsymbol{d_i} - \boldsymbol{e_i} - \mathbf{2}\boldsymbol{h_i}$) for each aircraft to guarantee that all baggage pieces are transported to the corresponding aircraft before the aircraft departs, as required by Constraint (9). This leads to Property 1.

Property 1. *A feasible solution* $\{\boldsymbol{y_{ilt}}, \boldsymbol{v_t}, \boldsymbol{b_{it}}\}, \forall \boldsymbol{i} \in \mathscr{I}, \boldsymbol{l} \in \mathscr{L}, \boldsymbol{t} \in \mathscr{T}$ *to problem (1)-(10) must satisfy*

$$\sum_{l\in\mathscr{L}} \sum_{t'=g_i}^{d_i-e_i-2h_i} \boldsymbol{y}_{ilt'} \geq \mathbf{1}$$

Further, all MVs heading to aircraft $\boldsymbol{i}$ must be dispatched within its effective dispatch period, i.e., the period between the first baggage piece's arrival time, denoted as $\boldsymbol{a_i}$, and latest dispatch time (i.e., $\boldsymbol{d_i} - \boldsymbol{e_i} - \mathbf{2}\boldsymbol{h_i}$) of aircraft $\boldsymbol{i}$. We denote this period by $\mathbb{E}_i$. Thus, we have the following Property 2.

Property 2. *Denote the check-in time for the first baggage piece heading to aircraft* $\boldsymbol{i}$ *by* $\boldsymbol{a_i}$. *A feasible solution* $\{\boldsymbol{y_{ilt}}, \boldsymbol{v_t}, \boldsymbol{b_{it}}\}, \forall \boldsymbol{i} \in \mathscr{I}, \boldsymbol{l} \in \mathscr{L}, \boldsymbol{t} \in \mathscr{T}$ *to problem (1)-(10) must satisfy*

$$\sum_{i\in\mathscr{I}, l\in\mathscr{L}} \sum_{t'=1}^{a_i} \boldsymbol{y}_{ilt'} = \mathbf{0},$$

and

$$\sum_{i\in\mathscr{I}, l\in\mathscr{L}} \sum_{t'=d_i-e_i-2h_i+1}^{T} \boldsymbol{y}_{ilt'} = \mathbf{0}$$

Next, we briefly review the theoretical properties of the GHG emission function f_{il}, which were originally proved in (Chen et al., 2019) for general operational cost with a concave function form. Because of the economics of scale of the GHG emission function in this study, the following two properties thus hold.

Property 3. *For* f_{il} *as a concave function of* l, *we obtain* $f_{il_1} + f_{il_2} + \cdots + f_{il_n} \geq f_{i(l_1+l_2+\cdots+l_n)}, \forall i \in \mathscr{I}, l_1, l_2, \cdots, l_n \in \mathscr{L}, l_1 + l_2 + \cdots + l_n \in \mathscr{L}, n \in \mathbb{Z}^+$

Property 4. *For* f_{il} *as a concave function of* l, *we obtain* $f_{il_1} + f_{il_4} \leq f_{il_2} + f_{il_3}, \forall i \in \mathscr{I}, l_1 \leq l_2 \leq l_3 \leq l_4 \in \mathscr{L}$ and $l_1 + l_4 = l_2 + l_3$ (Chen et al., 2019).

These properties provide insights into the relationships among the GHG emissions of MVs composed of different numbers of MCs. Specifically, Property 3 reveals that combining short MVs into longer ones reduces GHG emissions. Property 4 reveals that for given a short MV and a long MV, regrouping the MCs in these MVs into two MVs, both no shorter than the originally short MV and no longer than the originally long MV, will not increase the total GHG emissions.

3.2. Construction-merging heuristic

Fig. 6 provides an overview of the proposed construction-merging heuristic. It consists of two algorithms. First, a feasible MV dispatching schedule construction algorithm (Algorithm 1, see Section 3.2.1) is proposed to generate a feasible solution to the studied problem. Next, a MV dispatching schedule merging algorithm (Algorithm 2, see Section 3.2.2) is proposed to further improve the solution by modifying the feasible solution generated by Algorithm 1. By following the steps shown in Fig. 6, a feasible solution to the MV scheduling problem is obtained. This feasible solution takes advantage of the properties of the problem and, thus, often yields a near-optimal objective value, even if not guaranteeing the exact optimality of the constructed solution. Note that to ensure the feasibility of the solution, the MV dispatch time is fixed in Algorithm 2, which may restrict the optimality of the final solution. However, numerical experiments indicate that the proposed construction-merging heuristic has fairly good performance in obtaining satisfactory green MV scheduling solutions (see Section 4 for the results). The remaining of this section presents the two algorithms in the construction-merging heuristic.

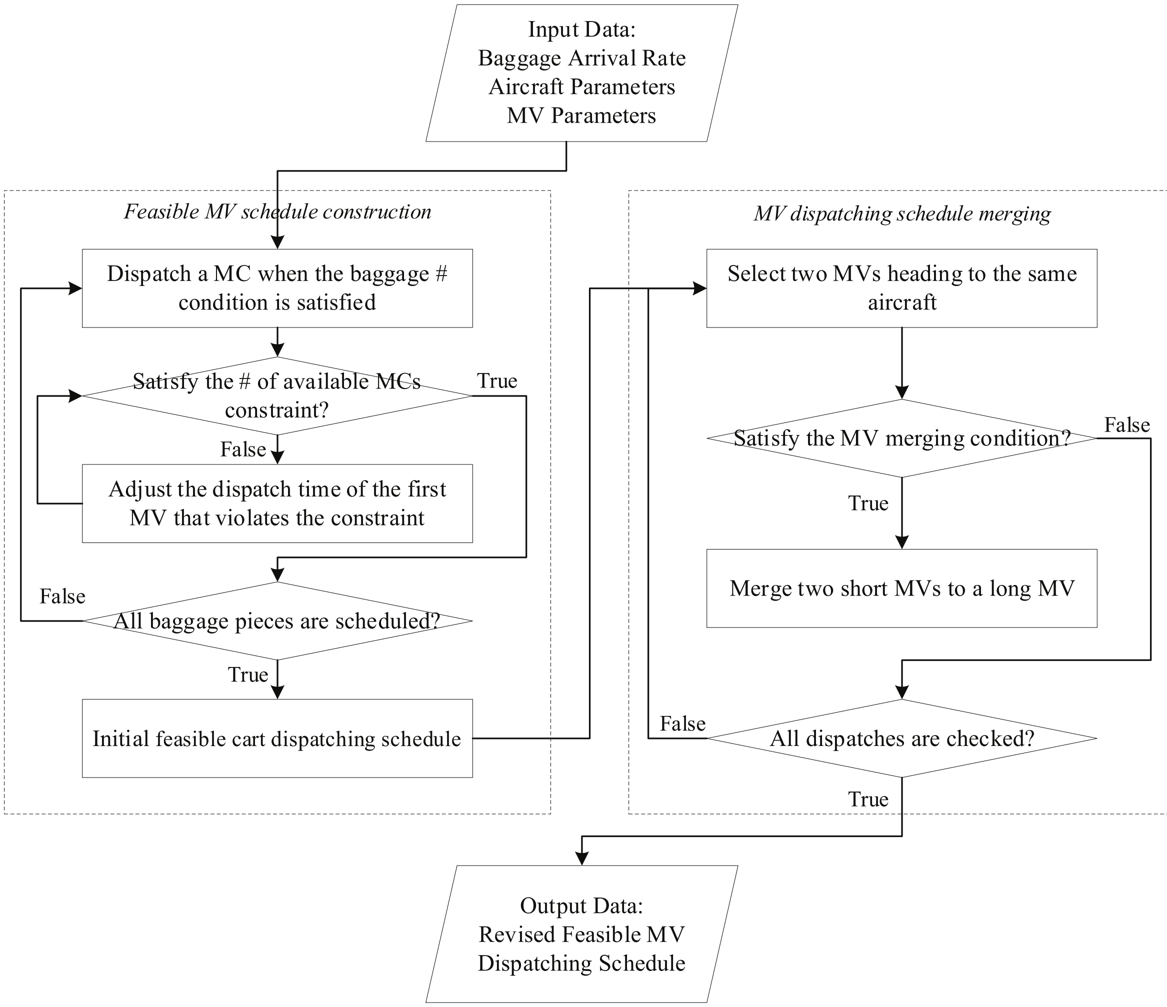

Fig. 6. Overall flowchart of the proposed construction-merging heuristic algorithm.

3.2.1. Feasible MV dispatching schedule construction

Based on Properties 1–2, a feasible solution to the green MV scheduling problem can be constructed by dispatching a series of 1-MC MVs (i.e., MVs with only one MC) within the effective dispatch period for each aircraft (i.e., $\mathbb{E}_i\ \forall i \in \mathcal{I}$). This solution construction process is motivated by the well-known savings algorithm for the VRP problem (Clarke and Wright, 1964), with modifications (Steps 6 and 7) made to ensure a feasible solution can be found for the investigated problem. The basic idea is to dispatch a 1-MC MV as long as the number of baggage pieces waiting to be transported at the terminal is greater than the capacity of a single MC unit.

To develop this algorithm, we define the waiting baggage queue as the number of baggage pieces waiting to be transported to aircraft i until time interval t. This queue can be formulated as $s_{it} := \sum_{t'=1}^{t}(p_{it'} - b_{it'})$, $\forall t \in \mathcal{T}$, where s_{it} denotes the waiting baggage queue heading to aircraft i at time interval t. For example, assume that the numbers of check-in baggage are $\{1,2,3\}$ for the first three time intervals, respectively. If no baggage is transported in these three time intervals, the waiting baggage queues are $\{1,3,6\}$ for the three time intervals, respectively. If a MV with 5 spaces is dispatched at time interval 2, the numbers of the waiting baggage queue then become $\{1,0,3\}$ for these three time intervals, respectively. With this definition, a feasible MV dispatching schedule is constructed as follows (the pseudo-code of this algorithm is given in Algorithm 1 in Appendix B).

Step 1: Initialize $i = 1$. Input the number of check-in baggage pieces for aircraft i at time interval t (i.e., $p_{it}, \forall i \in \mathcal{I}, t \in \mathcal{T}$) and the capacity for one MC (i.e., c), and set the initial number of MCs available (i.e., V) to a sufficiently large value. For baggage heading to aircraft i, input the effective dispatch period (i.e., $\mathbb{E}_i, \forall i \in \mathcal{I}$) and the latest check-in time (i.e., $g_i, \forall i \in \mathcal{I}$).
Step 2: Update s_{it} with the up-to-date $\{b_{it}\}$. Find the earliest time interval t_1 in the effective dispatch period of aircraft i (Property 2) whose cumulative waiting baggage is greater than or equal to the capacity of one MC (i.e., c), i.e., $t_1 := \underset{t \in \mathbb{E}_i}{\mathbf{argmin}}\{t \mid s_{it} - c \geq 0\}, \forall i \in \mathcal{I}$ and then dispatch a 1-MC MV at the next time interval, i.e., $y_{i1(t_1+1)} = 1, b_{i(t_1+1)} = c$.
Step 3: Repeat Step 2 until the largest waiting baggage queue is less than the capacity of one MC, i.e., $\underset{t \in \mathbb{E}_i}{\mathbf{max}}\{s_{it}\} < c$. Then, dispatch a 1-MC MV at the latest baggage check-in time if there is baggage left (Property 1), i.e., if $s_{ig_i} > 0, y_{i1g_i} = 1$, which ensures that all baggage pieces heading to aircraft i are transported.
Step 4: Check the number of MCs available (i.e., v_t) within $\mathcal{T}$. If $v_t \geq 0, \forall t \in \mathcal{T}$, go to Step 5; otherwise, go to Step 6.
Step 5: If $i \neq I$, $i = i + 1$, go to Step 2; otherwise, a feasible MV dispatching schedule y_{ilt} is found.
Step 6: If $v_t \geq 0, \forall t \in \mathcal{T}$, go to Step 5; otherwise, identify the earliest time t_2 when the number of MCs available is less than 0, i.e., $t_2 := \underset{t \in \mathcal{T}}{\mathbf{argmin}}\{t | v_t < 0\}$. Check whether the MV dispatched at time $t_2 - 1$ can be dispatched later at $t_3 \in \{\mathbb{E}_i \setminus \{a_i, a_i + 1, \cdots, t_2 - 1\}\}$ satisfying $v_t \geq \hat{v}_t \geq 0, \forall t \in \{t_3 + 1, t_3 + 2, \cdots, t_3 + 2e_i + 2h_i\}$, i.e., $t_3 = \underset{t \in \mathbb{E}_i \setminus \{a_i, a_i+1, \cdots, t_2-1\}}{\mathbf{min}}\{\mathbf{arg}\{t | v_t \geq 0, t \in \{t_3 + 1, t_3 + 2, \cdots, t_3 + 2e_i +$

$\boldsymbol{2h_i}\}\}$. If yes, go to Step 7; otherwise, output no feasible solution was found.

Step 7: Assume $\boldsymbol{l'}$ MCs are dispatched at time $\boldsymbol{t_2-1}$, (i.e., $\boldsymbol{l'} = \sum_{l\in\mathscr{L}} \boldsymbol{l}\cdot\boldsymbol{y}_{\boldsymbol{il(t_2-1)}}$), and $\boldsymbol{l''}$ MCs are dispatched at time $\boldsymbol{t_3}$ (i.e., $\boldsymbol{l''} = \sum_{l\in\mathscr{L}} \boldsymbol{l}\cdot\boldsymbol{y}_{\boldsymbol{ilt_3}}$). Then if $\boldsymbol{l'}+\boldsymbol{l''}\le \boldsymbol{L}$, cancel both the MVs dispatched at $\boldsymbol{t_2-1}$ and $\boldsymbol{t_3}$ (i.e., set $\boldsymbol{y}_{\boldsymbol{il''t_3}} = \boldsymbol{0}$ and $\boldsymbol{y}_{\boldsymbol{il'(t_2-1)}} = \boldsymbol{0}$), and dispatch a new MV at time $\boldsymbol{t_3}$ with $\boldsymbol{l''}+\boldsymbol{l'}$ MCs (i.e., set $\boldsymbol{y}_{\boldsymbol{i(l''+l')t_3}} = \boldsymbol{1}$). Go to Step 6.

To facilitate the understanding, a toy example for constructing the MV schedule of two aircraft is given as follows. Assume that the effective dispatch period for the first aircraft is time intervals 1–10, and the numbers of check-in baggage for these intervals are $\{\mathbf{1},\mathbf{3},\mathbf{5},\mathbf{3},\mathbf{1},\mathbf{1},\mathbf{3},\mathbf{5},\mathbf{3},\mathbf{1}\}$, respectively. The effective dispatch period for the second aircraft is time intervals 6–15, and the numbers of check-in baggage for these intervals are $\{\mathbf{1},\mathbf{2},\mathbf{3},\mathbf{4},\mathbf{5},\mathbf{5},\mathbf{4},\mathbf{3},\mathbf{2},\mathbf{1}\}$, respectively. The capacity for one MC is 10, and the number of MCs in stock is 2. For illustration purposes, we assume that the sum of handling and traveling time are two time intervals, such that the dispatched MCs can be reused after two time intervals. As shown in Fig. 7, the numbers in the squares are the number of check-in baggage at each time interval, and the numbers below them are the cumulative waiting baggage defined above. Based on the proposed solution construction process, 1-MC MVs are dispatched at the earliest time interval in the effective dispatch period of each aircraft whose cumulative waiting baggage is greater than or equal to the capacity of one MC (i.e., 10) (marked in red). In addition, 1-MC MVs are dispatched at the latest baggage check-in time for the two aircraft, respectively. The numbers of available MCs in stock at each time interval are shown at the bottom in Fig. 7. It can be seen that the number of available MCs is nonnegative in the studied horizon, indicating the feasibility of the constructed MV scheduling solution.

3.2.2. MV dispatching schedule merging

Based on Properties 3 and 4, the objective value of a schedule constructed in the previous section can be further decreased by merging short MVs into longer MVs. To minimize the impact of the merging operation on the previous aircraft, we propose a backward merging algorithm that starts the merging process from the last aircraft $\boldsymbol{I}$ until the schedules of all aircraft are revised. For notation convenience, we denote $\mathscr{K}_{\boldsymbol{i}} = \{\boldsymbol{k_{i1}},\boldsymbol{k_{i2}},\cdots,\boldsymbol{k_{iJ_i}}\}$ as the set of dispatch times for all MVs heading to aircraft $\boldsymbol{i}$, where $\boldsymbol{k_{ij}}$ is the dispatch time of the $\boldsymbol{j}$-th MV heading to aircraft $\boldsymbol{i}$ and $\boldsymbol{J_i}$ is the number of MVs dispatched to aircraft $\boldsymbol{i}$. The MV dispatch schedule mering algorithm is as follows (the pseudocode of this algorithm is given in Algorithm 2 in Appendix B.)

Step 1: Initialize $\boldsymbol{i} = \boldsymbol{I}$. Input the constructed MV dispatching schedule $\boldsymbol{y}_{\boldsymbol{ilt}}, \forall \boldsymbol{l}\in\mathscr{L}, \boldsymbol{t}\in\mathbb{E}_{\boldsymbol{i}}$ and the number of MCs available at time $\boldsymbol{t}$ (i.e., $\boldsymbol{v_t}$, $\forall \boldsymbol{t}\in\mathscr{T}$), which can be calculated by plugging $\boldsymbol{y}_{\boldsymbol{ilt}}$ into Equations (3) and (4).

Step 2: Check the number of MVs dispatched to aircraft $\boldsymbol{i}$ (i.e., $\boldsymbol{J_i}$). If $\boldsymbol{J_i} = \boldsymbol{1}$, go to Step 5; otherwise, initialize $\boldsymbol{j} = \boldsymbol{1}$, and go to Step 3.

Step 3: Update $\boldsymbol{v_t}, \forall \boldsymbol{t}\in\mathscr{T}$ (i.e., number of MCs available at $\boldsymbol{t}$). Check whether the $\boldsymbol{j}$-th dispatched MV can be merged with the $\boldsymbol{j'}$-th, $\boldsymbol{j'}\in\{\boldsymbol{J_i},\cdots,\boldsymbol{j}+\boldsymbol{1}\}$ dispatched MV without influencing the feasibility of $\boldsymbol{v_t}$ and $\boldsymbol{y}_{\boldsymbol{ilt}}$ (i.e., Properties 3 and 4). Assume $\boldsymbol{l'}$ MCs are dispatched at time $\boldsymbol{k_{ij'}}$ (i.e., $\boldsymbol{l'} = \sum_{l\in\mathscr{L}} \boldsymbol{l}\cdot\boldsymbol{y}_{\boldsymbol{ilk_{ij'}}}$), and $\boldsymbol{l''}$ MCs are dispatched at time $\boldsymbol{k_{ij}}$ (i.e., $\boldsymbol{l''} = \sum_{l\in\mathscr{L}} \boldsymbol{l}\cdot\boldsymbol{y}_{\boldsymbol{ilk_{ij}}}$). Check if $\boldsymbol{v_{t'}} \ge \boldsymbol{l''}, \forall \boldsymbol{t'}\in\{\boldsymbol{k_{ij'}},\cdots,\boldsymbol{k_{ij'}}+\boldsymbol{2e_i}+\boldsymbol{2h_i}\}$ and $\boldsymbol{l'}+l''\le L$. If yes, cancel both the j th and j' th MVs (i.e., set $y_{il''k_{ij}} = 0$ and $y_{il'k_{ij'}} = 0$), and dispatch a new MV at time $k_{ij'}$ with $l''+l'$ MCs (i.e., set $y_{i(l''+l')k_{ij'}} = 1$); otherwise, go to Step 5.

Step 4: If $j \ne J_i - 1$, $j = j+1$, go to Step 3; otherwise, go to Step 5.

Step 5: If $i \ne 1$, $i = i-1$, go to Step 2; otherwise, a revised MV dispatching schedule $\hat{y}_{ilt}$ is found.

The example in the previous subsection is used here again to facilitate the understanding of the algorithm. Based on the results obtained from the previous example specified in Fig. 7, three 1-MC MVs are dispatched for aircraft 1 at times 5, 9, 11, and three 1-MC MVs are dispatched for aircraft 2 at times 10, 12, 16. With the above revision algorithm, the schedule of aircraft 2 is revised first. By looping between Step 3 and Step 5, it can be found that the first dispatched MV can be merged to the third dispatched MV without influencing the feasibility of v_t and y_{ilt}. Thus, in the revised schedule of aircraft 2, the second dispatched MV remains the same, and the first dispatched MV is canceled and merged with the third dispatched MV. As a result, a 1-MC MV is dispatched at time 12, and a 2-MC MV is dispatched at time 16 for aircraft 2. In a similar way, the schedule of aircraft 1 is revised. However, for aircraft 1, the first dispatched MV cannot be merged with the third dispatched MV because v_t at time 13 would be otherwise negative. Then, we can try to merge the first dispatched MV to the second MV and find it is feasible without incurring negative v_t values. Therefore, for aircraft 1, the first dispatched MV is canceled, a 2-MC MV is dispatched at time 11, and the third dispatched MV is kept the same. Finally, the revised dispatching schedule $\hat{y}_{ilt}$ is found. Other decision variables, such as the number of available MCs at time t (i.e., $\hat{v}_t$), and the number of transported baggage destined for aircraft i at time t (i.e., $\hat{b}_{it}$) can be obtained accordingly by plugging $\hat{y}_{ilt}$ into Equations (1)–(10).

4. Numerical experiments

The proposed green MV scheduling optimization model is a linear integer programming model. Thus, Gurobi was used as a benchmark solver against the proposed construction-merging heuristic. Gurobi was chosen because it is one of the most advanced commercial solvers for integer programming and has been widely utilized in many studies (Bertsimas et al., 2021; Chen et al., 2019, 2020; Li, 2014). Both the proposed construction-merging heuristic and Gurobi were coded in Visual Studio 2019 with C++ as the programming language. The computer platform is a Windows 10 PC with Intel Xeon E3-1275 CPU and 32.0 GB RAM.

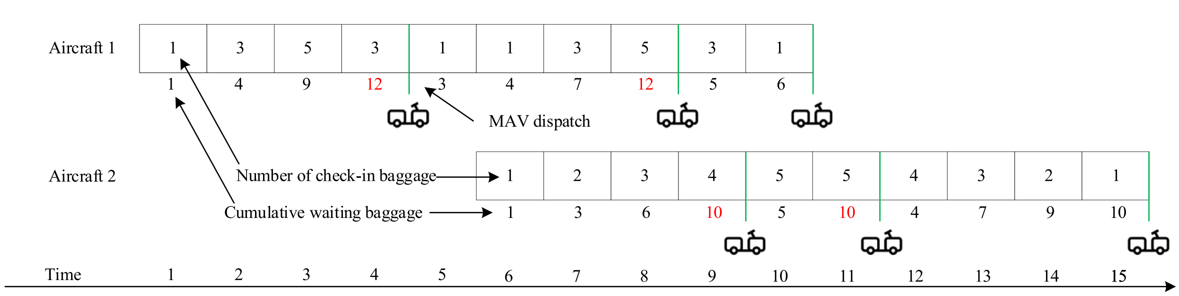

Fig. 7. Illustration of feasible solution construction process.

4.1. Experiment settings

To test the feasibility and validity of the optimization model and to assess the performance of the proposed algorithm, numerical experiments were conducted with data collected from TPA. The case study background, data collection method, and evaluation approach are described below.

TPA is an international airport in Tampa, Florida. It is the 28th busiest airport by passenger movement in North America, with an average of 58,3127 passengers daily and an average of 17,728 checked baggage (TPA, 2019). There are six active terminals, but only four (Terminals A, C, E, F) were in operation when the study was being conducted. Among them, Terminal C is the largest and only had one airline operating on the study date. This provided an excellent testbed for studying the proposed design. Fig. 8 is a map of Terminal C, showing 16 gates scattered around the terminal.

Three types of data were collected for the experiments, including baggage arrival, GHG emission-related data, and time-relevant data, as follows.

- As the actual baggage arrival information was unavailable at the planning stage, flight schedule information (Table 2) was used to populate the baggage arrival process via simulation. Please refer to Appendix A for details regarding passenger arrival simulation. The simulation generated the baggage arrival rate, with three values of w, which represents the probability of a passenger carrying a baggage that needs to be checked in, as shown in Fig. 9. It was found that our simulation results are consistent with peak airport hours, as detailed by Travel Codex (2018) . This consistency supports the reliability of our simulation methodology in replicating actual passenger flow and baggage demand.
- GHG emission-related data were collected as follows. By referring to the parameters of standard four-wheel baggage carts, the capacity for one MC (i.e., c) was set as 20 baggage pieces. The fuel consumption parameters (i.e., C^F, C^V, and α) and the coefficient to convert fuel consumption to GHG emissions (i.e., w) were obtained from Power (2020), with $C^F = 20.2$ kg/h, $C^V = 0.6$, $\alpha = 0.5$. In addition, the initial number of available MCs at the terminal (i.e., V) was set to 8.
- Time-related data were collected as follows. From TPA's official website, the latest check-in time is 30 min before the scheduled departure time (www.tampaairport.com). Travel time between the terminal and aircraft (i.e., e_i) was obtained by measuring the travel distance from the terminal to each gate. Assuming that the travel speed of the MC is 15 mph, travel times were estimated as shown in Table 3. The handling time was assumed to be 1 min.

4.2. Experiment results

This section presents results from the experiments to evaluate our proposed MV operation model and heuristic algorithm from various aspects and to provide managerial and operational insights. Specifically, Section 4.2.1 compares the computational performance of our construction-merging heuristic against a benchmark solver. In Section 4.2.2, we discuss the adaptability of the proposed MV operation across different operational scenarios including idle, normal, busy, and mixed, highlighting its flexibility and efficiency in varying contexts. Section 4.2.3 focuses on the reduction of GHG emissions achieved by the proposed MV operation compared to traditional operations that utilize fixed-capacity vehicles. Lastly, Section 4.2.4 examines the application of the proposed MV operation across different airports, considering variations in fleet size, vehicle numbers, and baggage arrival demands. This section demonstrates the scalability and adaptability of our approach, emphasizing its potential applicability in diverse airport settings.

4.2.1. Comparison between the Gurobi solver and the proposed heuristic

This section compares the solutions obtained by the Gurobi solver and the heuristic with instances generated from the TPA data introduced above. The purpose is to evaluate the computational performance of the proposed heuristic. To better illustrate the parameter settings of each instance, an instance index, *I-L*, is used, in which I, L, respectively, represent the number of aircraft scheduled and the maximum number of MCs allowed in one MV. Twenty instances were generated for the experiments, each solved by both the Gurobi solver and the proposed heuristic. To compare the qualities of the solutions, the objective value (i.e., GHG emissions), solution time, and optimality gap were recorded. In addition, the maximum CPU time is limited to 7200 s, and after that time, we stopped the Gurobi solver or heuristic to output the best results. Table 4 exhibits the results obtained by the two methods. Instances that could not be solved by the Gurobi solver within the maximum CPU time are marked with "/" in Table 4. As we mentioned in Section 3, the solution optimality cannot be theoretically guaranteed by the proposed

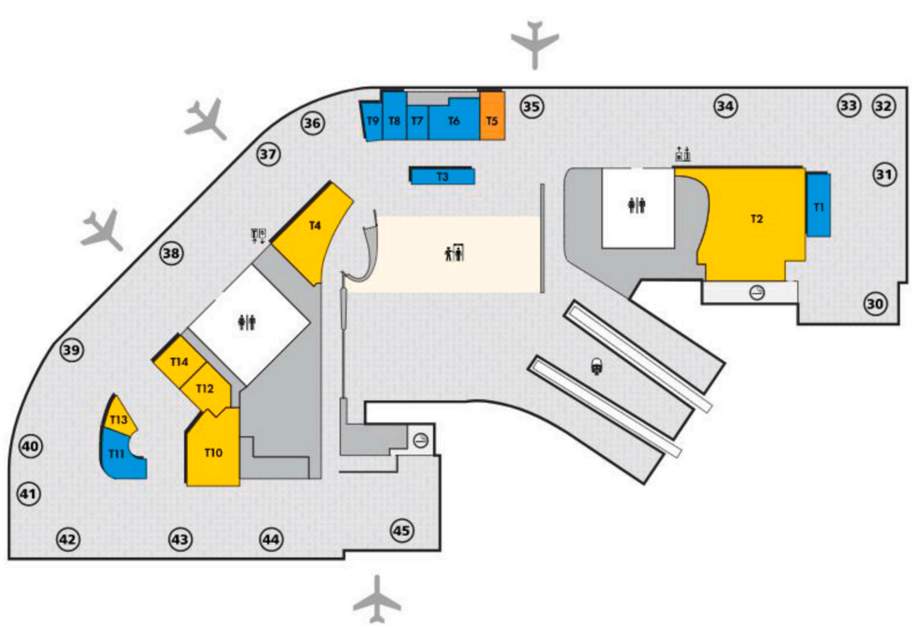

Fig. 8. Map of terminal c, TPA (source: www.tampaairport.com).

Table 2
Departure time and assigned gate for each aircraft.

Departure time	Gate	Departure time	Gate	Departure time	Gate	Departure time	Gate
6:55	C34	10:25	C36	14:00	C38	17:40	C35
7:50	C33	10:40	C33	14:10	C36	17:55	C31
8:15	C39	11:00	C44	14:20	C39	18:30	C37
8:45	C34	11:05	C37	14:25	C35	18:40	C35
9:00	C33	11:40	C35	14:25	C33	18:50	C33
9:05	C39	12:10	C44	15:00	C37	19:00	C31
9:10	C31	12:10	C32	15:35	C40	21:00	C31
9:15	C35	12:25	C33	15:35	C35	21:05	C35
9:25	C32	12:35	C36	15:45	C33	21:25	C33
10:00	C38	12:40	C43	16:00	C31	21:40	C37
10:15	C39	13:30	C37	16:40	C37	22:00	C31
10:20	C30	13:50	C31	17:05	C39	22:10	C43
10:25	C34	14:00	C34	17:40	C33		

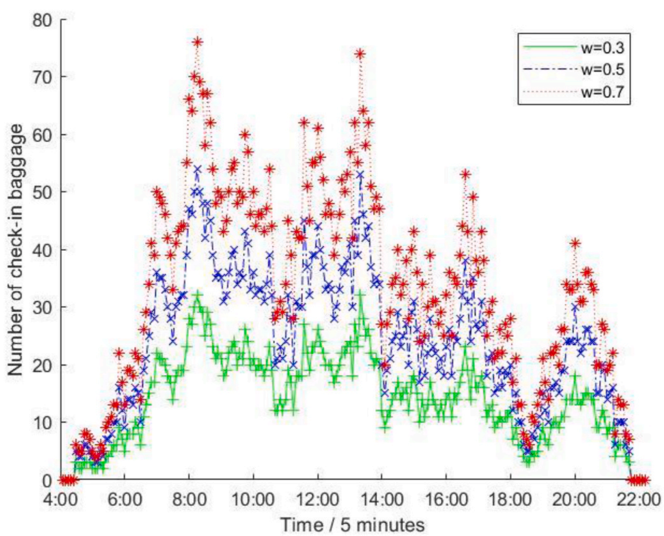

Fig. 9. Simulated baggage arrival rate for all flights over one day with different values of *w*.

Table 3
Travel time between the terminal and each gate.

Gate	C30	C31	C32	C33	C34	C35	C36	C37
Travel time/min	1	1	1	1	1	1	2	2
Gate	C38	C39	C40	C41	C42	C43	C44	C45
Travel time/min	2	2	2	2	3	3	3	3

heuristic. However, for the instances solved by the Gurobi solver (those with an optimality gap of 0), the objective values (i.e., GHG emissions) generated by the heuristic are identical. Meanwhile, for each instance, the solution time for the proposed heuristic is much shorter than that of the Gurobi solver, which indicates much better solution efficiancy of the proposed heuristic. With such a short solution time, the proposed heuristic provides more robustness and flexibility to airport schedule managers and planners. Also, the solution time for the Gurobi solver is highly related to the instance scale (i.e., the number of variables), which indicates that the Gurobi solver lacks scalability in solving the investigated problem. In contrast, the heuristic solves all instances within relatively short time (less than 200ms), and the increase in its solution time over the problem instance size is rather moderate.

4.2.2. Effectiveness of the proposed MV operation

This section assesses the effectiveness of the proposed MV operation in decreasing the GHG emissions for airport departure baggage transportation. We generated four scenarios with different baggage arrival patterns (i.e., idle, normal, busy, and mixed). The first three scenarios assume that the probability of a passenger carrying a piece of baggage (a parameter used in the baggage arrival simulation process; see Appendix A) is the same across all aircraft. This setting can benefit the demonstration of the proposed model with different scenarios but may not be the case for real-world operations, in which the baggage arrival rate for each aircraft is heterogeneous. Thus, a mixed scenario was generated with heterogeneous baggage arrival rates to test the performance of the proposed model further. The "greenest" MV dispatching plans obtained

Table 4
Comparisons of the solution results between Gurobi and the proposed heuristic.

Instance Index	# of variables	Method	GHG emissions (kg/day)	Solution time (second)	Gap
51–1	112270	Gurobi	829.3	7200	0.30%
		heuristic	829.3	0.18	/
41–1	69305	Gurobi	666.7	3542	0.00%
		heuristic	666.7	0.12	0.00%
31–1	36375	Gurobi	504.1	2577	0.00%
		heuristic	504.1	0.08	0.00%
21–1	21715	Gurobi	341.5	682	0.00%
		heuristic	341.5	0.05	0.00%
11–1	8625	Gurobi	178.9	191	0.00%
		heuristic	178.9	0.02	0.00%
51–2	167860	Gurobi	586.4	7200	0.21%
		heuristic	586.4	0.1	/
41–2	103540	Gurobi	471.4	4361	0.00%
		heuristic	471.4	0.07	0.00%
31–2	58750	Gurobi	356.4	3264	0.00%
		heuristic	356.4	0.05	0.00%
21–2	32320	Gurobi	241.5	869	0.00%
		heuristic	241.5	0.02	0.00%
11–2	12750	Gurobi	126.5	257	0.00%
		heuristic	126.5	0.01	0.00%
51–3	223450	Gurobi	/	7200	/
		heuristic	489.9	0.07	/
41–3	137775	Gurobi	396.0	7200	0.25%
		heuristic	396.0	0.05	/
31–3	78125	Gurobi	300.3	3551	0.00%
		heuristic	300.3	0.03	0.00%
21–3	42925	Gurobi	202.7	960	0.00%
		heuristic	202.7	0.03	0.00%
11–3	16875	Gurobi	103.2	261	0.00%
		heuristic	103.2	0.01	0.00%
51–4	279040	Gurobi	/	7200	/
		heuristic	471.9	0.1	/
41–4	172010	Gurobi	/	7200	/
		heuristic	379.4	0.05	/
31–4	97500	Gurobi	286.8	7200	0.10%
		heuristic	286.8	0.04	/
21–4	53530	Gurobi	194.3	4666	0.00%
		heuristic	194.3	0.02	0.00%
11–4	21000	Gurobi	101.8	392	0.00%
		heuristic	101.8	0.01	0.00%

from the proposed design for the first three scenarios (i.e., idle, normal, busy) are plotted in Fig. 10, each dot representing a MV dispatched to transport the baggage from the unloading area to the aircraft. Table 5 summarizes several key indicators of the system for all scenarios.

As shown in Fig. 10, the sizes of the dispatched MVs vary for different dispatches, demonstrating the effectiveness of introducing modular operations in airport baggage transportation. Further, as seen in Table 5, the greenest MV dispatch plans are consistent with the baggage arrival pattern. That is, it is desirable to dispatch more vehicles (and the total number of MCs) when the system is busy, and fewer MCs are needed when the system is relatively idle. In addition, the maximum numbers of operating MCs for the busy, normal, and idle scenarios are all 8, meaning that no MCs are available at the terminal in some time intervals for all the scenarios (which can be observed in Fig. 10). However, due to the relatively sparse baggage arrival rates in the idle and normal scenarios, the numbers of such time intervals in these two scenarios are fewer than in the busy scenario, as seen in Fig. 10. As the GHG emissions are correlated with the number of dispatched MVs of each type, the busy scenario has the highest GHG emissions, and the next is the normal scenario, followed by the idle scenario. The type of MVs dispatched for the busy, normal, idle scenarios is {3,4}, {2,4}, {4}, respectively, showing that two types of MVs (i.e., a MV with 3 or 4 MCs) are dispatched for the busy scenario, two types for the normal scenario, and only one for the idle scenario. This is, again, due to the different baggage demand rates. For example, for the idle scenario, one MV with 4 MCs is sufficient to transport all baggage from the terminal to the corresponding aircraft. However, for the busy scenario, one MV with 4 MCs is not enough; thus, an MV with 3 MCs is employed to transport the rest of the baggage. Finally, in the mixed scenario, the proposed paradigm can transport all baggage to the corresponding aircraft by dispatching three types of MAVs. The maximum number of operating MCs for the mixed scenario is 8.

Table 5
Summary of key statistics from the proposed design.

Scenario	# of dispatched MVs	# of dispatched MCs	Dispatched MV types	Max. # of MCs available	GHG emissions (kg/day)
Busy	102	357	{3,4}	8	519.5
Normal	102	306	{2,4}	8	471.9
Idle	51	204	{4}	8	276.4
Mixed	113	377	{2,3,4}	8	550.7

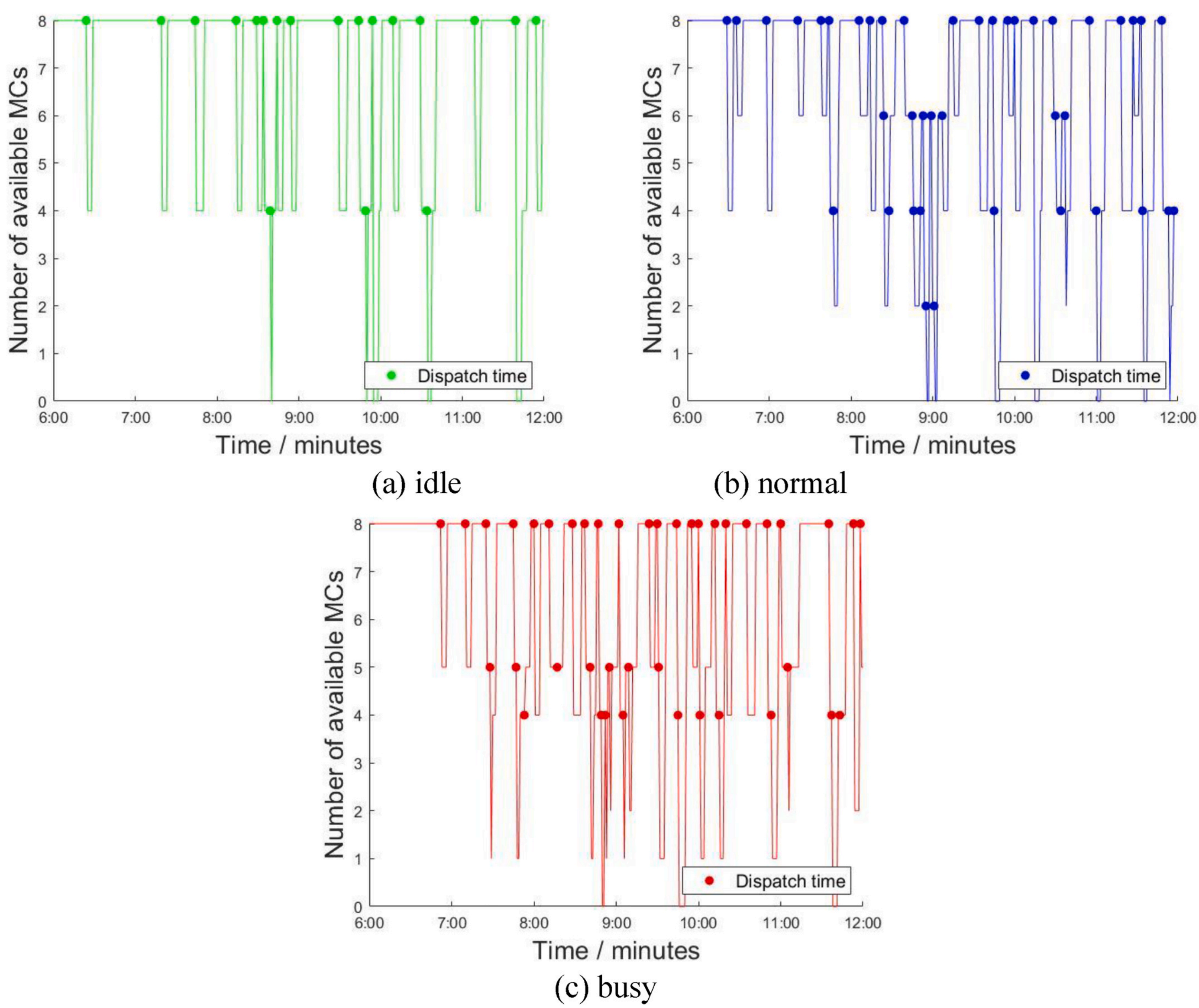

Fig. 10. MV dispatch plans with different simulated baggage arrival rates.

4.2.3. Comparison with the fixed-capacity operation

To understand the performance of the proposed MV operation on reducing GHG emissions, several key system outputs were compared between the proposed MV operation and the existing fixed-capacity operation. In the existing fixed-capacity operation, the dispatched MV types were fixed, and four vehicle types consisting of 1–4 MCs were considered. The results are summarized in Table 6, which shows that the proposed MV operation always yields lower daily GHG emissions than the existing operation with fixed vehicle types. In particular, in the idle scenario where the vehicle type is set as 1, the daily GHG emissions of the existing operation are almost three times that of the proposed MV operation, which reveals the huge potential of MV technology to reduce GHG emissions for airport departure baggage transportation. Additionally, the number of MVs and MCs dispatched in the proposed MV operation is not greater than that of the existing operation, meaning that there is no need to purchase extra MCs to implement the proposed operation. Indeed, in many of the studied cases, the number of MCs dispatched was lower than needed in the existing operation, meaning that the proposed operation can reduce fleet size and save the costs relevant to the vehicle fleet, e.g., management and maintenance costs. In addition, in Table 6, we assumed the assembly and disassembly time for MVs is relatively short, which reflects the ultimate performance of emerging MV technologies. However, the MV operation concept can immediately benefit the existing fixed-capacity operational paradigm by asking the ground crew to manually assemble and disassemble the MVs. The comparison of emissions reduction performance as MV technologies develop can be found in Appendix C.

The economy of scale (quantified by α) is a critical factor that affects the extent to which MVs can reduce GHG emissions. For example, the higher the travel speed, the more aerodynamic drag will be reduced, thus the higher the extent of the economy of scale. Because the travel speed of ground vehicles in airports is relatively low (e.g., 15 mph) compared with typical vehicle platooning scenarios, it is thus necessary to investigate the sensitivity of MV's capability in reducing GHG emissions to the economy of scales. To this end, in the normal scenario, we compared the proposed MV operation with the existing fixed-capacity operational paradigm (1-MC and 4-MCs) under various degrees of the economy of scale (i.e., α). The results are summarized in Fig. 11, using the percent reduction in GHG emissions as the evaluation metric (a negative value indicates a reduction). We observe that the proposed modular operation persistently decreases the GHG emissions across all α values (as indicated by the negative value on the vertical axis), suggesting that the proposed MV-based operation persistently decreases GHG emissions for departure flight baggage transportation even though the value of α varies. However, as the value of α increases, the percent reduction in GHG emissions exhibits decreasing trends (as indicated by the decreasing absolute value of the percent reduction), meaning that if the degree of the economy of scales decreases, the effectiveness of the proposed MV operation in reducing GHG emissions also reduces. This finding implies that airport operators should carefully evaluate the degree of the economy of scale in their baggage transportation activities before investing in these MV technologies. However, there are no empirical studies on the economy of scale of MVs and thus we leave such an evaluation for future studies.

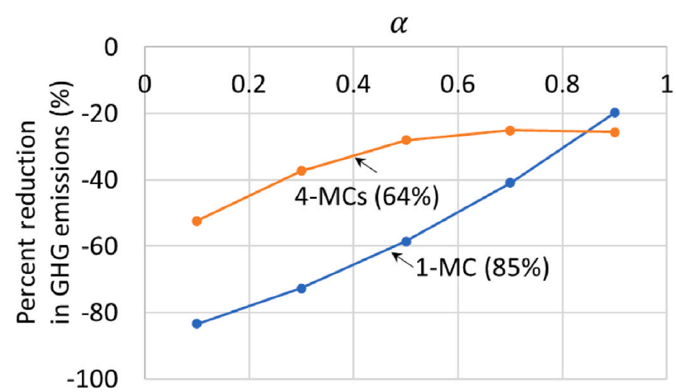

Fig. 11. Comparison between the existing fixed-capacity operational paradigm and proposed modular solution with varying economies of scale (quantified by parameter α). Number in parenthesis represents the average percentage of empty space across all dispatches in a solution.

4.2.4. Sensitivity analysis

A sensitivity analysis was conducted on several input parameters to explore further whether the proposed MV operation can still reduce GHG emissions in other airports when the input parameters may not be the same as those of this study. In each experiment, only one parameter was varied, and the other parameters remained the same at their default values. The number of dispatched MVs, MCs, and the overall GHG emissions were used as the evaluation criteria. Sensitivity analysis results over parameters including the maximum number of MCs in one MV (i.e., L), the initial number of MCs available at the terminal (i.e., V), the capacity for one MC (i.e., c), and the probability of a passenger carrying a piece of baggage (i.e., w) that determines the number of check-in baggage pieces (i.e., p_{it}) are plotted in Fig. 12.

Fig. 12 (a)–(b) shows that as the maximum number of MCs allowed in one MV increases, the number of MVs dispatched decreases, but the number of MCs dispatched remains the same. This is because the number of arrival baggage is constant; thus the number of MC units needed to serve the demand remains the same. However, each MV can accommodate more MCs, so the number of MVs naturally decreases. Because of the economics of scale of the GHG emissions with respect to the number of MCs in a MV, the GHG emissions reduce as the MV becomes longer, as shown in Fig. 12 (c).

As shown in Fig. 12 (d)–(e), the number of MCs dispatched does not vary as the number of MCs available changes. This is, again, because the

Table 6
Comparison between the existing fixed-capacity operational paradigm and proposed modular solution over a typical operational day.

Scenario	MV type	Existing fixed-capacity operational paradigm			Proposed modular solution		
		# of dispatched MVs	# of dispatched MCs	GHG emissions (kg/day)	# of dispatched MVs	# of dispatched MCs	GHG emissions (kg/day)
Busy	1	357	357	1325.7	102	357	519.5
	2	204	408	986.6			
	3	153	459	871.7			
	4	102	408	655.2			
Normal	1	306	306	1136.3	102	306	471.9
	2	153	306	739.9			
	3	102	306	581.1			
	4	102	408	655.2			
Idle	1	204	204	757.6	51	204	276.4
	2	102	204	493.5			
	3	102	306	581.1			
	4	51	204	327.6			

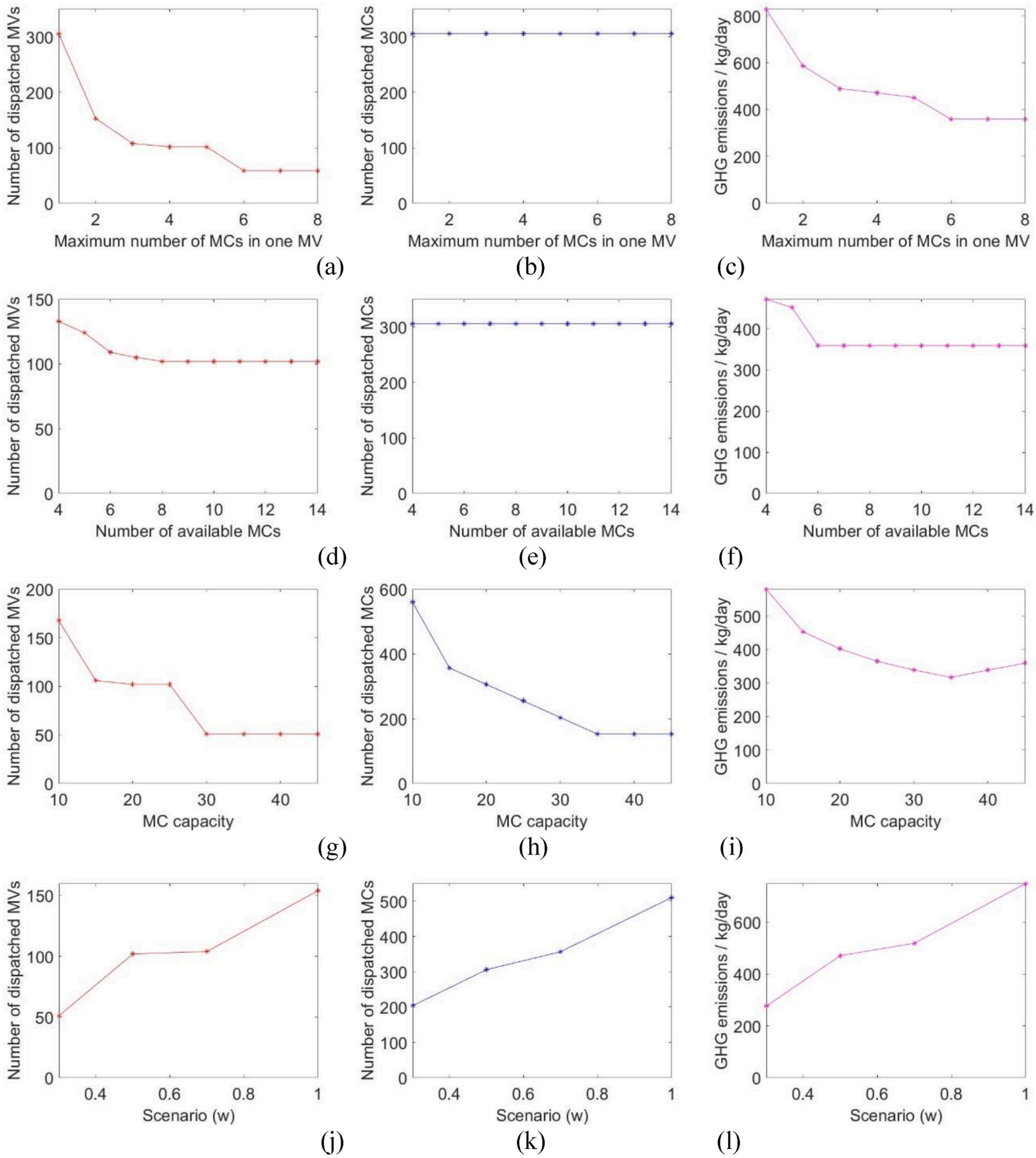

Fig. 12. Sensitivity analysis to $L, V, c,$ and w.

baggage arrival rate does not change, and the MCs are already sufficient to serve all demand in the base case. However, the number of MVs decreases as the number of available MCs changes from 4 to 8, because a larger number of long MVs can be formed with more MCs. Dispatching a larger number of longer MVs reduces GHG emissions, as shown in Fig. 12(f). However, the changes only happen when the number of MCs available is less than 8. As can be seen in Table 5, the maximum number of operating MCs is 8, which indicates that 8 MCs are needed to achieve the optimal operation schedule of the proposed MV-operation. Because the changes will not influence the number of arrival baggage in the number of available MCs, the number of dispatched MCs remains the same over different numbers of available MCs. Thus, a further increase in the number of MCs available does not improve the performance.

As shown in Fig. 12 (h), the number of MCs dispatched decreases as the MC capacity increases. The reason is intuitive - if the number of arrival baggage is constant, the larger the capacity of one MC is, the fewer MCs are needed to transport the baggage as more baggage can be accommodated by one MC. This also decreases the number of MVs dispatched, as shown in Fig. 12 (g). However, Fig. 12 (i) reveals that the GHG emissions decrease as the MC capacity increases at the beginning. Later on, the GHG emissions increase as the MC capacity keeps increasing. This is because once a single MV dispatch can transport all baggage pieces to the corresponding aircraft, further increasing the MC capacity increases the overall vehicle weight, but the number of baggage pieces being transported is the same. Thus, more energy is consumed to power the MV to move, and more GHG emissions are generated. Here, an extreme situation can be imagined in which the capacity of a MC is infinite. To satisfy the baggage transportation requirement, a 1-MC MV needs to be dispatched at the latest check-in time for each aircraft. The number of dispatched MVs and MCs are equal to the number of aircraft (i.e., I) in this situation, respectively.

Finally, Fig. 12 (j)–(k) shows that as the probability of a passenger carrying baggage increases, so does the number of MCs, the number of MVs, and the GHG emission. These results can be easily understood because the larger the probability of a passenger carrying baggage, the greater the amount of baggage required to be transported, and thus, the greater the number of MVs and MCs that will be dispatched.

5. Conclusions

This study proposed a new solution for airport departure baggage transportation with the emerging MV technologies. The problem was rigorously formulated into a linear integer programming model that aimed to minimize the GHG emissions of baggage transportation vehicles. Due to the excessive solution time and poor scalability of existing linear programming solvers on this problem, a construction-merging heuristic was proposed based on the theoretical properties of the investigated problem. A series of case studies using data from TPA were conducted to evaluate the necessity and validity of the proposed MV operation and the effectiveness of the proposed algorithm. The results indicate that the proposed MV operation effectively reduces the GHG emissions for airport departure baggage transportation compared with existing operations across a range of parameter settings. Moreover, the proposed heuristic can obtain near-optimal solutions much faster than that of the Gurobi solver without much loss of the optimality of the solutions.

Although only baggage for departure flights is investigated in this study, the modular operation applies to incoming flights and other ground transportation vehicles (e.g., those transporting food). Thus, the results in this study demonstrate the potential of the emerging MV technologies in decarbonizing airport baggage transportation and, more broadly, ground vehicle operations at airports. This study also provides models and algorithms that airport designers and operators can adopt to derive green baggage transportation solutions in practice. Future research can be conducted in several directions. In this study, only one baggage transportation provider was considered. However, in practice, multiple airline companies usually undertake baggage transportation, and their cooperation can be integrated into future studies. In addition, in the current problem settings, it was assumed that each dispatch serves only one aircraft; it would be interesting to consider that each dispatch can serve more than one aircraft before it returns to the terminal. Also, this study only investigates MV scheduling with predicted baggage arrival rates. A natural next step is to incorporate demand stochastics in the model. Finally, the construction-merging heuristic is proposed based on the special structure of the investigated problem. It would be a good theoretical effort to explore the structure of the problem further to enhance the algorithm or investigate some exact algorithms for the problem.

CRediT authorship contribution statement

Xiaowei Shi: Conceptualization, Formal analysis, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Zhiwei Chen:** Conceptualization, Formal analysis, Software, Visualization, Writing – original draft, Writing – review & editing. **Xiaopeng Li:** Conceptualization, Funding acquisition, Writing – review & editing. **Xiaobo Qu:** Conceptualization, Writing – review & editing.

Acknowledgments

This research was sponsored by U.S. National Science Foundation Grants CMMI #2313835 and Airport Cooperative Research Program (ACRP) University Design Competition (Second Place winner). Comments and concepts from NEXT Future Transportation, Inc. are appreciated. A preliminary report can be found on the webpage of the ACRP Design Competition (https://vsgc.odu.edu/acrpdesigncompetition/).

Appendix A. Baggage arrival demand simulation

Step 1. Information was collected on flight schedules for a typical weekday (April 13th, 2020) from TPA's official website, as summarized in Table 2. A total of 51 aircraft was scheduled to depart from the terminal from 06:55 a.m. to 10:10 p.m.
Step 2. The airline company at Terminal C mainly offers domestic services. Thus, Boeing 737 and 757 are the most often used aircraft models. The capacity of these models (i.e., around 200 passengers/aircraft) was used to estimate the number of customers.
Step 3. As all passengers do not necessarily travel with check-in baggage, parameter w is introduced to represent the probability of a passenger carrying a baggage that needs to be checked in. Multiplying the number of passengers in each aircraft and w yields an estimation of the number of baggage pieces for each aircraft.
Step 4. In the literature, the passenger arrival process at airports follows specific distributions (e.g., normal, Weibull, Poisson, etc.). After searching the major literature, it was found that a commonly-used passenger arrival rate distribution is the Poisson distribution (Ashford et al., 1976). Thus, the baggage arrival process was simulated as a Poisson process.

Note that certain assumptions had to be made in the simulation process due to data limitations. For example, we assumed that the aircraft would be fully occupied, using the seating capacities of Boeing 737 and 757 as estimates for the number of passengers. In reality, the number of passengers could be less than the capacity. Furthermore, we used a parameter w to estimate the proportion of passengers with baggage, though it's possible for one passenger to have multiple pieces of baggage. While these simplifications introduce biases in estimating the baggage arrival count, they are sufficient for generating insights in a proof-of-concept study. With access to more detailed data in the future, more sophisticated models could be developed to more accurately reflect airport dynamics and better estimate passenger and baggage counts.

Appendix B. Pseudo codes for the construction-merging heuristic

Algorithm 1. Feasible MV dispatching schedule construction.

Input $\mathcal{I}; \mathcal{T}; \mathcal{L}; c; \mathbb{E}_i, a_i, g_i, \forall i \in \mathcal{I}; s_{it}, p_{it}, \forall i \in \mathcal{I}, t \in \mathcal{T}$
For $i = 1$ to I **do**
For $t = a_i$ to g_i **do**
If $s_{it} - c \geq 0$
$y_{i1(t+1)} = 1, b_{i(t+1)} = c$
update s_{it} by $s_{it} \coloneqq p_{it} + \sum_{t'=1}^{t-1}(p_{it'} - b_{it'}), \forall t \in \mathcal{T}$
End if
End for
If $s_{ig_i} > 0$
$y_{i1g_i} = 1$
End if
For $t = 1$ to T **do**
If $v_t < 0$
$t_2 = \arg\min_{t \in \mathcal{T}}\{t|v_t < 0\}, t_3 = \min_{t \in \mathbb{E}_i \backslash \{a_i, a_i+1, \cdots, t_2-1\}}\{\arg\{t|v_t \geq 0, t \in \{t_3+1, \cdots, t_3+2e_i+2h_i\}\}\}$
If $t_3 \neq \emptyset$
$l' = \sum_{l \in \mathcal{L}} l \cdot y_{il(t_2-1)}, l'' = \sum_{l \in \mathcal{L}} l \cdot y_{ilt_3}$
If $l' + l'' \leq L$
$y_{il''t_3} = 0, y_{il'(t_2-1)} = 0, y_{i(l''+l')t_3} = 1$
End if
Else
Output no feasible solution
End if
End if
End for
End for
Output The feasible MV dispatching schedule y_{ilt}

Algorithm 2. MV dispatching schedule merging.

Input $\mathcal{I}; \mathcal{T}; \mathcal{L}; y_{ilt}; v_t; e_i, h_i, \mathcal{K}_i, J_i, \forall i \in \mathcal{I}$
For $i = I$ to 1 **do**
If $J_i > 1$
For $j = 1$ to $J_i - 1$ **do**
For $j' = J_i$ to $j + 1$
$l' = \sum_{l \in \mathcal{L}} l \cdot y_{ilk_{ij'}}, l'' = \sum_{l \in \mathcal{L}} l \cdot y_{ilk_{ij}}$
If $v_{t'} \geq l'', \forall t' \in \{k_{ij'}, \cdots, k_{ij'} + 2e_i + 2h_i\}$ and $l' + l'' \leq L$
$y_{il''k_{ij}} = 0, y_{il'k_{ij'}} = 0, y_{i(l''+l')k_{ij'}} = 1$
End if
End for
End for
End if
End for
Output The revised MV dispatching schedule $\hat{y}_{ilt}$

Appendix C. Emissions reduction performance comparison as MV technologies develop

In our previous analysis, we assumed the assembly and disassembly time for MVs is relatively short, which reflects the ultimate performance of emerging MVs. To understand the performance when the carts are assembled and disassembled manually, we can adjust the model to include specific idle times for internal combustion engines during each dispatch, accommodating the additional time required for manual assembly and disassembly processes. For reference, the GHG emissions from a typical internal combustion engine during idle time are approximately 10,180 g of GHG emissions per gallon of diesel (Lafayette College's Emissions Overview, 2024). With this, we provide the following GHG emissions for human-driven carts with different engine idle times, such as 5 min, 2 min, and 1 min, using the instances in Subsection 4.2.3. Our results illustrate that as MV technology advances, reducing the time required for assembly and disassembly processes, the environmental performance of the MV solution can be further improved in terms of GHG emissions reduction.

Scenario	MV type	Fixed-capacity Solution	Proposed MV with human-driven carts (5 min)	Proposed MV with human-driven carts (2 min)	Proposed MV with human-driven carts (1 min)	Proposed MV solution
		GHG emissions (kg/day)	GHG emissions (kg/day)	GHG emissions (kg/day)	GHG emissions (kg/day)	GHG emissions (kg/day)
Busy	1	1325.70	527.0	522.5	521.0	519.5
	2	986.6				
	3	871.7				
	4	655.2				
Normal	1	1136.30	479.4	474.9	473.4	471.9
	2	739.9				
	3	581.1				
	4	655.2				
Idle	1	757.6	280.2	277.9	277.2	276.4
	2	493.5				
	3	581.1				
	4	327.6				

References

Ashford, N., Hawkins, N., O'Leary, M., Bennetts, D., McGinity, P., 1976. Passenger Behavior and design of airport terminals. Transport. Res. Rec. 18–26.

ATAG, 2011. Website: https://seors.unfccc.int/applications/seors/attachments/get_attachment?code=AD75PKPBLWIRYBI18OTM7MF6SZ584E4E#:~:text=We/20will/20improve/20our/20fleet,annum/20between/20now/20and/202020.&text=from/202020/2C/20net/20carbon/20emissions,capped/20through/20carbon/2Dneutral/20growth.&text=By/202050/2C/20net/20aviation/20carbon,what/20they/20were/20in/202005.

Ben Cheikh, N., Ben Zaied, Y., Chevallier, J., 2021. On the nonlinear relationship between energy use and CO2 emissions within an EKC framework: evidence from panel smooth transition regression in the MENA region. Res. Int. Bus. Finance 55, 101331. https://doi.org/10.1016/j.ribaf.2020.101331.

Bertsimas, D., Ng, Y.S., Yan, J., 2021. Data-driven transit network design at scale. Oper. Res. 0–16 https://doi.org/10.1287/opre.2020.2057.

Chen, Z., Li, X., 2021. Designing corridor systems with modular autonomous vehicles enabling station-wise docking: discrete modeling method. Transport. Res. Part E Logist. Transp. Rev. https://doi.org/10.1016/j.tre.2021.102388.

Chen, Z., Li, X., Zhou, X., 2019. Operational design for shuttle systems with modular vehicles under oversaturated traffic: discrete modeling method. Transp. Res. Part B Methodol. 122, 1–19. https://doi.org/10.1016/j.trb.2019.01.015.

Chen, Z., Li, X., Zhou, X., 2020. Operational design for shuttle systems with modular vehicles under oversaturated traffic: continuous modeling method. Transp. Res. Part B Methodol. 132, 76–100. https://doi.org/10.1016/j.trb.2019.05.018.

Chunyu, L., Zain-ul-Abidin, S., Majeed, W., Raza, S.M.F., Ahmad, I., 2021. The nonlinear relationship between carbon dioxide emissions, financial development and energy consumption in developing European and Central Asian economies. Environ. Sci. Pollut. Res. https://doi.org/10.1007/s11356-021-15225-2.

Clarke, G., Wright, J.R., 1964. Scheduling of vehicle routing problem from a central depot to a number of delivery points. Oper. Res. 12, 568–581. https://doi.org/10.1287/opre.12.4.568.

Daganzo, C.F., 1996. Logistics Systems Analysis. Springer, Berlin Heidelberg, Berlin, Heidelberg. https://doi.org/10.1007/978-3-662-03196-4.

Dai, Z., Cathy, X., Chen, X., Ma, X., 2020. Joint optimization of scheduling and capacity for mixed traffic with autonomous and human-driven buses : a dynamic programming approach. Transport. Res. Part C 114, 598–619. https://doi.org/10.1016/j.trc.2020.03.001.

Elffers, J., 2018. Scheduling with two non-unit job lengths is NP-complete. https://arxiv.org/pdf/1412.3095.pdf.

Federal Aviation Administration, 2022. Source. https://www.faa.gov/regulations_policies/policy_guidance/envir_policy/airquality_handbook.

Fontaras, G., Zacharof, N.G., Ciuffo, B., 2017. Fuel consumption and CO2 emissions from passenger cars in Europe – laboratory versus real-world emissions. Prog. Energy Combust. Sci. 60, 97–131. https://doi.org/10.1016/j.pecs.2016.12.004.

Fontela, P., Soria, A., Mielgo, J., Sierra, J.F., de Blas, J., Gauchia, L., Martínez, J.M., 2007. Airport electric vehicle powered by fuel cell. J. Power Sources 169, 184–193. https://doi.org/10.1016/j.jpowsour.2007.01.056.

Forbes, J., 2019. The Move to Make Airport Baggage Trucks More Efficient. Source. https://www.fluxpower.com/blog/the-move-to-make-airport-baggage-trucks-more-efficient.

Guo, Q.W., Chow, J.Y.J., Schonfeld, P., 2018. Stochastic dynamic switching in fixed and flexible transit services as market entry-exit real options. Transport. Res. C Emerg. Technol. 94, 288–306. https://doi.org/10.1016/j.trc.2017.08.008.

Hassold, S., Ceder, A.A., 2014. Public transport vehicle scheduling featuring multiple vehicle types. Transp. Res. Part B Methodol. 67, 129–143. https://doi.org/10.1016/j.trb.2014.04.009.

Helber, S., Broihan, J., Jang, Y., Hecker, P., Feuerle, T., 2018. Location planning for dynamic wireless charging systems for electric airport passenger buses. Energies 11, 258. https://doi.org/10.3390/en11020258.

Howards, S., 2001. Airport-Based Alternative Fuel Vehicle Fleets (No. NREL/FS-540-28353). National Renewable Energy Lab.(NREL), Golden, CO (United States).

Huang, E., Liu, I., Lin, J.T., 2018. Robust model for the assignment of outgoing flights on airport baggage unloading areas. Transportation Research Part E: Logistics and Transportation Review 115, 110–125.

Huang, E., Mital, P., Goetschalckx, M., Wu, K., 2016. Optimal assignment of airport baggage unloading zones to outgoing flights. Transportation research part E: logistics and transportation review 94, 110–122.

Johnstone, M., Creighton, D., Nahavandi, S., 2010. Status-based Routing in Baggage Handling Systems: Searching Verses Learning. IEEE Trans Syst. Man Cybernetics, Part C 40 (2), 189–200.

Lafayette College's Emissions Overview, 2024. Source. https://sites.lafayette.edu/egrs352-sp14-cars/impacts-on-sustainability/ghg-emissions/.

Lee, D.S., Fahey, D.W., Skowron, A., Allen, M.R., Burkhardt, U., Chen, Q., Doherty, S.J., Freeman, S., Forster, P.M., Fuglestvedt, J., Gettelman, A., De León, R.R., Lim, L.L., Lund, M.T., Millar, R.J., Owen, B., Penner, J.E., Pitari, G., Prather, M.J., Sausen, R., Wilcox, L.J., 2021. The contribution of global aviation to anthropogenic climate forcing for 2000 to 2018. Atmos. Environ. https://doi.org/10.1016/j.atmosenv.2020.117834.

Li, J.Q., 2014. Transit bus scheduling with limited energy. Transport. Sci. 48, 521–539. https://doi.org/10.1287/trsc.2013.0468.

Li, X., 2022. Source. https://catslab.engr.wisc.edu/.

Lin, J.T., Shih, Ping-Hsi, Huang, E., Chiu, C., 2015. Airport baggage handling system simulation modeling using SysML. In: 2015 International Conference on Industrial Engineering and Operations Management (IEOM), Dubai, 2015, pp. 1–10.

Liu, Y., Wu, J., Tang, J., Wang, W., Wang, X., 2022. Scheduling optimisation of multi-type special vehicles in an airport. Transp. Build. https://doi.org/10.1080/21680566.2021.1983484.

Lodewijks, G., Cao, Y., Zhao, N., Zhang, H., 2021. Reducing CO emissions of an airport baggage handling transport system using a particle swarm optimization algorithm. IEEE Access. https://doi.org/10.1109/ACCESS.2021.3109286.

Mo, P., Yang, L., Wang, Y., Qi, J., 2019. A flexible metro train scheduling approach to minimize energy cost and passenger waiting time. Comput. Ind. Eng. 132, 412–432. https://doi.org/10.1016/j.cie.2019.04.031.

NEXT, 2018. Source. https://www.next-future-mobility.com/.

Peeters, P., Higham, J., Kutzner, D., Cohen, S., Gössling, S., 2016. Are technology myths stalling aviation climate policy? Transport. Res. Transport Environ. https://doi.org/10.1016/j.trd.2016.02.004.

Power, P., 2020. Fuel Cell Powered Airport GSE (Ground Support Equipment) Deployment. Source. https://www.osti.gov/servlets/purl/1606013.

Scherr, Y.O., Neumann-Saavedra, B.A., Hewitt, M., Mattfeld, D.C., 2018. Service network design for same day delivery with mixed autonomous fleets. Transport. Res. Procedia 30, 23–32. https://doi.org/10.1016/j.trpro.2018.09.004.

Scherr, Y.O., Neumann Saavedra, B.A., Hewitt, M., Mattfeld, D.C., 2019. Service network design with mixed autonomous fleets. Transport. Res. Part E Logist. Transp. Rev. 124, 40–55. https://doi.org/10.1016/j.tre.2019.02.001.

Shi, X., Li, X., 2021. Operations design of modular vehicles on an oversaturated corridor with first-in, first-out passenger queueing. Transport. Sci. https://doi.org/10.1287/trsc.2021.1074.

Shi, X., Chen, Z., Pei, M., Li, X., 2020. Variable-capacity operations with modular transits for shared-use corridors. Transp. Res. Rec. J. Transp. Res. Board. https://doi.org/10.1177/0361198120928077.

Sun, X., Yin, Y., 2019. Behaviorally stable vehicle platooning for energy savings. Transport. Res. C Emerg. Technol. https://doi.org/10.1016/j.trc.2018.12.017.

Travel Codex, 2018. The Busiest Time at the Airport. Source. https://www.travelcodex.com/understanding-airport-pulse-times/.

Tampa International Airport, 2019. Source: https://www.tampaairport.c.om/sites/default/master/files/Final/20FY2020/20Budget_All_Files_Combined_V2_8.27.19_0.pdf.

van Enter, E., 2018. Energy Consumption of Baggage Handling Systems: Impact Assessment on the Effect of Taking into Account Energy Consumption during Preliminary Design Stage.

Vogel, P., 2010. Improving Sustainability of Conveyor Systems within Baggage Handling. Delft University of Technology, Delft, the Netherlands. Report no. 2010.TEL.7419.

Zeinaly, Y., Wang H, B., 2019. Routing and scheduling for a last-mile transportation system. Transport. Sci. https://doi.org/10.1287/trsc.2017.0753.

Zhang, T., Ouyang, Y., He, Y., 2008. Traceable air baggage handling system based on RFID tags in the airport. Journal of Theoretical and Applied Electronic Commerce Research 3 (1), 106–115.

Zhang, Z., Tafreshian, A., Masoud, N., 2020. Modular transit: using autonomy and modularity to improve performance in public transportation. Transport. Res. Part E Logist. Transp. Rev. https://doi.org/10.1016/j.tre.2020.102033.

Zhu, S., Sun, H., Guo, X., 2022. Cooperative scheduling optimization for ground-handling vehicles by considering flights' uncertainty. Comput. Ind. Eng. https://doi.org/10.1016/j.cie.2022.108092.

Pinedo, M.L., 2008. S*cheduling: Theory, Algorithms, and Systems. Springer Publishing Company*, Incorporated, 3rd edition, 2008. ISBN 0387789340, 9780387789347.