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Robust design for underground metro systems with modular vehicles

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ABSTRACT

The asymmetric demands of metro lines in megacities can cause high passenger wait times and substantial underutilization of vehicle capacity. The problem is difficult to address because of passenger flow uncertainties and random delays. We propose a modular transit system (MTS) that allows a metro fleet to be dynamically dissembled and assembled in identical modules (or carriages) on metro terminals. A formal formulation of this issue is provided with a nonlinear programming (NLP) model that considers train power, greenhouse gas emissions, wind resistance, and operational economics. Then, a linearization of the NLP further facilitates its fast solution. By utilizing numerical experiments based on Shenzhen Metro data, we illustrate the mathematical model's viability and confirm the model's usefulness in terms of the economic, low-carbon, and ecological consequences. Then, the robustness of the proposed model and the sensitivity analysis with various parameter values are reported.

1. Introduction

In contrast to private transport, public transport (such as buses, trams, light trains, and metros) is a mode of transportation for passengers employing group travel systems accessible to the general public (Wu et al., 2021). Most public transportation services follow predetermined routes with predetermined points of boarding and alighting. With set routes and predetermined timetables, they often charge a fixed cost for each trip (Guo et al., 2017). However, the asymmetric distribution of passenger demand across different periods is considered a tough and persistent transit operational problem in megacities, which causes either large passenger wait time costs or considerable vehicle capacity waste (Shi et al., 2020). Therefore, passenger flow uncertainty and random delays vie to make these problems harder to address (Wang et al., 2020).

The conflict between spatially and temporally shifting passenger demand and fixed capacity to deliver transportation is a challenge that has persisted for a long time in metro transportation in megacities. These tough and persistent metro operational problems cause massive passenger wait time costs or considerable vehicle capacity waste (Pei et al., 2021). As shown in Fig. 1, taking the Shenzhen Metro system as an example, the passenger arrival demand rates on a typical day of operation for a metro transport system exhibit substantial temporal changes. Some MT operators suggest providing peak- and off-peak-based schedules to fit the asymmetric distribution of passenger demand across different periods. However, although this technique enhances MT system service quality to some level, there are still unresolved issues (Niu and Zhou, 2013). During peak hours, the passenger arrival rate is so high that passengers may be required to wait for many trains before boarding. During off-peak hours, the number of passengers on the subway is sometimes small. This means that there is a low load percentage and wasted energy for fixed-capacity carriages. (Chen et al., 2019). This research proposes an effective operational strategy to solve the identified problems that concurrently optimize dispatch headways and carriage capacities. The study is based on metro terminal data and can be easily extended to other urban public transit systems.

NEXT Future Transport is attempting to revolutionize the method of transporting people and objects (Aleksandar et al., 2012; Ali-Eldin and Elmroth, 2021; Casadó et al., 2020; Qu et al., 2022; K. Zhu et al., 2022). This innovative smart transportation system is built on swarms of modular electric vehicles according to the modular vehicle concept advanced by the NEXT Future transport company (Next Future Transport, 2022). As seen in Fig. 2, each module may compose or decompose from other modules. Because of this adaptability, in-route transfers are possible, which improves the system capacity rate, reduces costs and traffic, and promotes passenger ubiquity while simultaneously

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improving passenger comfort.

Then, more new intelligent transit companies focused on these fields, as shown in Fig. 3. Ohmio, for example, is the modular transit system innovator from New Zealand, as shown in Fig. 2, which presented safe and effectively modular vehicles to eliminate human error, safely negotiating and avoiding obstacles. Ohmio vehicles have been designed and tested on many use-cases, including airports, hospitals, and schools in New Zealand, Australia, China, and South Korea.

This study assumes that the carriages in the MT system can be quickly decomposed from one subway train and composed to another. This feature enables the dynamic modification of vehicle capacity while the system is in operation (Hannoun and Menéndez, 2022). In this technique, not only can the service quality be enhanced significantly, but the energy efficiency may also be raised. The waiting costs for passengers may be reduced by increasing the frequency of dispatches while decreasing the total number of vehicle units and increasing load percentages while maintaining suitable capacity can reduce wasteful energy use.

In the beginning of studying this research topic, several studies attempted to solve asymmetric passenger demands and implemented combinations of efficiency, time cost savings, and congestion relief into flexible transit system design (Frei et al., 2017; Kim and Schonfeld, 2014, 2015; Koffman, 2004; Li and Quadrifoglio, 2010; Nourbakhsh and Ouyang, 2012). This work either has a limited type of bus capacity (e.g., large bus and small bus) or flexible schedule (e.g., demand response transit system) (Errico et al., 2013; Kim and Schonfeld, 2015; Koffman, 2004; Malucelli et al., 1999; Nourbakhsh and Ouyang, 2012; Qu et al., 2022).

In recent years, the rapid development of new developing modular transportation systems has inspired a growing number of studies, which has increased the overall number of research projects (Chen et al., 2020; Hannoun and Menéndez, 2022; Olovsson et al., 2022; Pei et al., 2021; Tian et al., 2022; Wu et al., 2021). In the context of public transit, modular transit is a highly automated development of flexible transit, where individual carriages are arranged according to demand. (Zhang et al., 2020). Guo et al., 2018 proposed an analytical model to calculate and compare the cost difference between flexible and fixed transit. This model also decides when combining two modular vehicles into one is more cost-effective. Furthermore, Chen et al., 2020, 2019 proposed both a continuous modeling method and a discrete model to solve joint design modular vehicle problems, and these works proved that it is possible for a modular public transportation system to be useful in shuttle systems in both heavily and less traveled areas. The modular transit system is further extended to a Y-shaped route with shared corridors in unsaturated traffic (Shi et al., 2020). Next, a bilevel optimization method is developed for minimizing passenger transfers during in-route transfers, and potential implementations and practices are discussed extensively. (Wu et al., 2021). In addition to passenger route assignment and fleet modularization, a transfer-based, individualized model for the bus network was designed (Gong et al., 2021). By optimizing passenger routes and improving transfer operations, this design helps tailor bus networks. Furthermore, an ideal operational strategy for vehicle formation at terminals over a multiperiod service time horizon is provided to offer insight into the design of transit services using modular cars (Tian et al., 2022).

To date, various modular transit system models have been adopted to improve public transit systems, e.g., bus systems and metro systems, and these methods have achieved good results (Caros and Chow, 2021; Chen et al., 2020, 2019, 2018; Guo et al., 2018; Pei et al., 2021; Shi et al., 2020; Zhang et al., 2020). However, two issues in existing studies need to be addressed.

- First, few research studies have considered passenger flow uncertainty and its random delays in modular transit systems. Most previous modular transit-related studies (Chen et al., 2019; Shi et al., 2020; Shi and Li, 2021) considered a deterministic number of passengers without random departure time delays.
- Second, previous studies have focused more on the waiting time cost or system operating cost (Pei et al., 2021; Shi et al., 2020; Shi and Li, 2021). However, the transit system's timetable design and the modular vehicles' scheduling also affect energy consumption, which has a more profound impact on the environment and economy. Established studies lack sufficient consideration of this aspect.

Therefore, considering the limitations of existing research, this study aims to enrich the literature on modular transit systems and improve the effectiveness and applicability of programming methods, proposing an exact nonlinear integer programming method. The following is a condensed summary of the most important contributions and discoveries of this study.

- First, a modular transit system (MTS) that allows a metro fleet to be dynamically disassembled and assembled in identical modules (or carriages) on metro terminals is modeled as a nonlinear optimization model, which can be extended to public transportation systems in general. This nonlinear model is then reformed to become an exact equivalence linearized MILP model, which can be quickly and easily solved with a commercial solver. Then, a robust optimization is proposed to offer guaranteed performance and smooth operation in the presence of uncertainty.

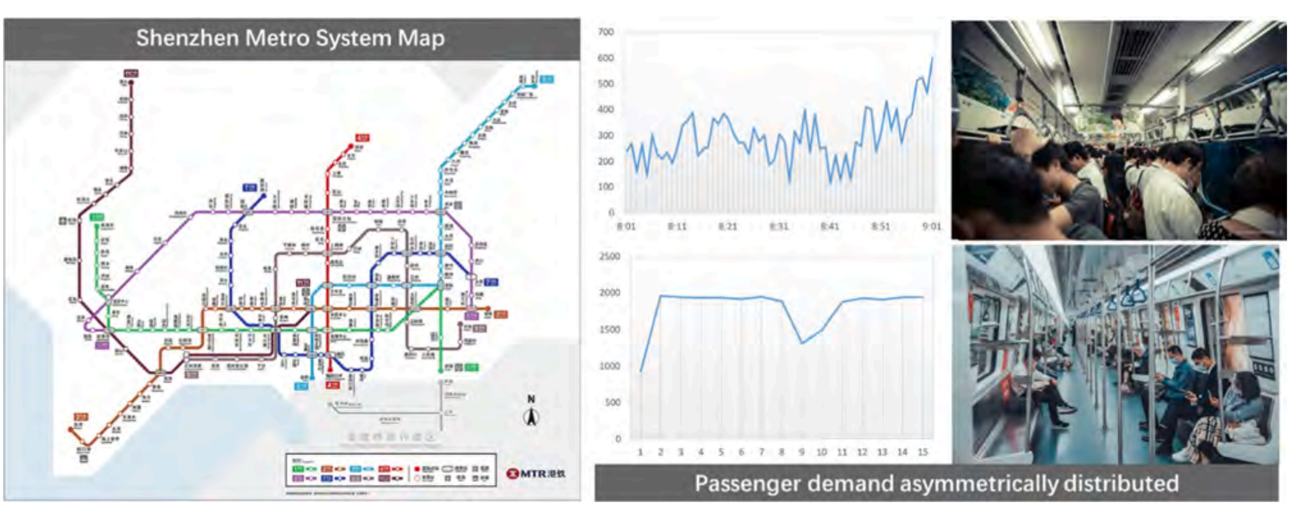

Fig. 1. Metro line passenger demand is asymmetrically distributed across different periods.

- Second, the passenger flow uncertainty and random delays are considered. Economical, low-carbon, and environmentally friendly effects are analyzed; more specifically, the train power energy, wind resistance, and operational economics are formulated. A sensitivity analysis is carried out to determine the primary elements that influence the operational design.

The rest of this work is organized as follows. The issue is broken down into its different parts in Section 2. Section 3 presents the problem formulation and the mathematical modeling using the linearization technique. In the fourth section of this paper, a case study of the Shenzhen Metro system and a discussion of the outcomes of the proposed model are presented. Section 5 discusses directions for future research.

2. Problem formulation

Table 1 provides a summary of the critical notation used throughout this study for the reader's convenience.

We consider a metro corridor with a total of I terminals in this study. Let set $\mathscr{I}:\{1,2,\cdots,i,\cdots,I\}$ represent the numbered terminals consecutively, in which $\mathscr{I}$ denotes the set of terminals and i is the terminal index. Then, the total research time horizons are divided into T slots, which have an equal length of δ. Let $\mathscr{T}:\{1,2,\cdots,t\cdots,T\}$ denote the discrete time points. For the duration of the operating horizon, passengers will continually arrive at each terminal. Passengers who arrive at terminal i at any given time slot $[t^{'}-1,t^{'}]$ traveling to terminal j are $p_{ijt'}$, $\forall i\in\mathscr{I},j\in\mathscr{I}_i^+,t'\in\mathscr{T}$, which is a random variable that follows a Poisson distribution. At every stop, the size of each train may be reselected from a carriage set $\mathscr{S}:[1,2,\cdots S]$, indexed as $s\in\mathscr{S}$, in which S represents the upper bound of the number of carriages that may be attached to a metro train. To provide service to these customers, the minimum headway that the trains are dispatched with is defined as H. Furthermore, the maximum number of passengers that may fit in one carriage is c.

In this study, we aim to determine how metro systems can operate most efficiently under investigation, considering factors, such as the amount of time needed for each dispatch and the total number of carriages present at each terminal reducing the system's overall cost. In line with prior research, this study investigates two aspects of cost for metro systems. We consider the total cost incurred in dispatching trains. The total cost comprises operating costs and passenger waiting time costs. The operating cost includes the depreciation cost of the system, the cost of energy consumption to overcome air resistance, and the cost of environmental pollution from CO2 emissions. Some of these operating costs are not related to the number of carriages carried on the train; for example, the cost of employing drivers does not increase with the number of carriages. Some are related to the number of carriages, e.g., the longer the train is, the greater the energy required to overcome aerodynamic drag.

The average vehicle operation cost that is unrelated to the number of carriages is denoted by the symbol C_{op}, whereas the operating cost per unit distance that depends on the number of carriages is denoted by the symbol C_s. The average passenger waiting time cost is the other component of the overall cost that we take into consideration. This metric is often used to assess the service level provided by metro systems.

Without the loss of generality, we believe that the system studied is consistent with the following assumptions.

Assumption 1. We assume that each terminal $i\in I$ is not allowed to be oversaturated. As soon as passengers arrive at a terminal, they should board the first arrived train.
Assumption 2. There is a constant time staying at terminals and a constant speed between terminals.
Assumption 3. We assume that all terminals have enough carriages. Consequently, we do not set a limit on the system's overall capacity. The ideal number of carriages may be found after solving the optimization model.

3. Methodology

3.1. Original formulation

3.1.1. Constraints on train operation

In contrast to the operations of conventional transit systems, the proposed metro system would allow carriage composition and decomposition at each terminal. To formulate this system-wide operational procedure, we first introduce the following decision variables:

- x_{tis}: binary variable, which equals 1 if the metro fleet with departure timed index t (departure time from the first terminal at time t) is dispatched from metro terminal i with s vehicles; otherwise, it equals 0.
- y_t: binary variable, which equals 1 if a vehicle departs from the first metro terminal at time t; otherwise, it equals 0.

The following are the operational limitations for the vehicle based on these two variables:

Uniform carriage number constraint

$$\sum_{s\in\mathscr{S}}x_{tis}=1,i\in\mathscr{I},t\in\mathscr{T} \tag{1}$$

Minimal headway constraint

$$\sum\nolimits_{t=t'}^{t'+h}y_t\le 1,1\le t^{'}\le T-h \tag{2}$$

Constraint (1) ensures that the number of carriages is unique between any two terminals, and Constraint (2) states that the minimum dispatch headway (i.e., h) cannot be less than the train-designed safety headway between two consecutive trains. Both of these constraints are in place to ensure that the metro system operates as safely as possible.

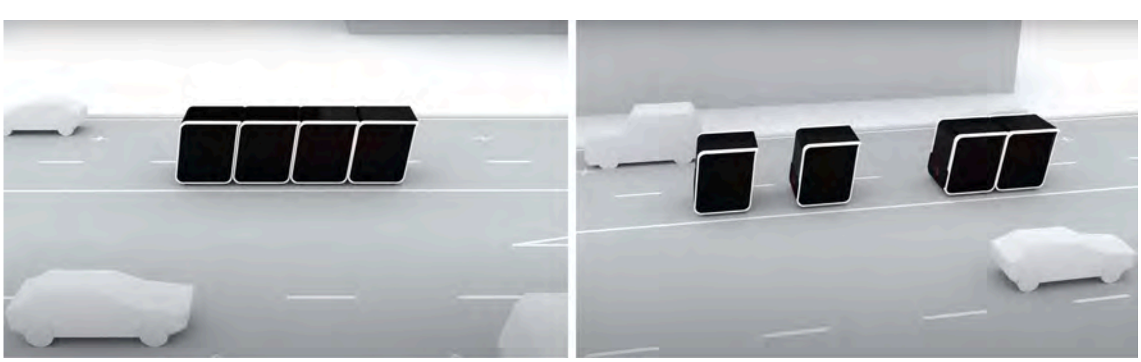

Fig. 2. Concept of a modular vehicle.

(a) NEXT Future Transport (b) Ohimo

(c) Future Road Infrastructure for DART (d) Keolis

Fig. 3. Overview of the existing modular transit vehicles. (a) NEXT Future Transport (source: http://www.next-future-mobility.com/); (b) Ohmio LIFT (source: https://ohmio.com); (c) Future Road Infrastructure for DART (Source: https://www.tum-create.edu.sg/); (d) Keolis (source: https://www. https://www.keoliscs.com/).

3.1.2. Constraints on travel demands

Passengers' actions on the proposed metro system have been considered. The following set of decision variables are included to capture passenger behavior.

$u_{ijt't}$: integer variable, the number of passengers arriving at metro terminal i and alighting to terminal j at time slot $[t'-1, t']$ and waiting for the subway train dispatched at time t.

$z_{ijt't}$: integer variable, the number of passengers boarding metro terminal i and alighting to terminal j at time slot $[t'-1, t']$ and waiting for the train dispatched at time t.

v_{ti}: Number of passengers leaving terminal i on the train dispatched at time t.

The following is a formulation of the passenger behavior utilizing these three factors.

Passenger transit service constraints

$$u_{ijt't} = z_{ijt't} y_t, \quad \begin{array}{c} 1 \le i < I, \\ i < j \le I, \\ 1 \le t' \le T, \\ 1 \le t \le T, \\ t + \Delta T_i > t' \end{array} \tag{3}$$

$$z_{ijt't} = p_{ijt'} - \sum_{t''=\max\{1, t'-\Delta T_i\}}^{t-1} u_{ijt't''}, \quad \begin{array}{c} 1 \le i < I, \\ i < j \le I, \\ 1 \le t' \le T, \\ 1 \le t \le T, \\ t + \Delta T_i > t' \end{array} \tag{4}$$

$$\sum_{1 \le t \le T} u_{ijt't} = p_{ijt'}, \quad i,j \in \mathcal{I}, 1 \le t' \le T \tag{5}$$

$$v_{ti} = v_{t,i-1} + \sum_{j > i, t + \Delta T_i > t'} u_{ijt't} - \sum_{j < i, t + \Delta T_i > t'} u_{jit't}, \quad t \in \mathcal{T}, i \in \mathcal{I} \tag{6}$$

$$v_{ti} \le \sum_{s \in \mathcal{S}} x_{tis} y_t cs, \quad t \in \mathcal{T}, i \in \mathcal{I} \tag{7}$$

Constraint (3) is imposed because overcrowding is not allowed, so all waiting passengers must be able to board the first train. According to Constraint (4), those who are waiting to board (i.e., $z_{ijt't}$) and those who have boarded (i.e., $u_{ijt't''}$) are all linked to each other by passenger demand (i.e., $p_{ijt'}$). Constraint (5) requires all the waiting passengers to finally be served within the operational horizon.

The behavior of passengers boarding and alighting the vehicle is the focus of Constraints (6) and (7). According to Constraint (6), the number of on-boarding passengers after a specific terminal is equal to the number of people who boarded at each previous terminal minus the number of people who left at each previous terminal. Vehicle composition and decomposition vary the calculation of available capacity across all terminals. Hence, we use Constraint (7) to determine the total capacity at each terminal.

3.1.3. Variable domains

The constraints listed below establish a feasible domain for each decision variable.

$$x_{tis}, y_t \in \mathbb{B}, \quad t \in \mathcal{T}, i \in \mathcal{I}, s \in \mathcal{S} \tag{8}$$

$$u_{ijt't}, z_{ijt't}, v_{ti} \in \mathbb{N}, \forall i \in \mathcal{I}, j \in \mathcal{I}_i^+, t' \le t + \Delta T_i \in \mathcal{T}, t \in \mathcal{T} \tag{9}$$

A set of domain constraints connected to operating are specified in Constraint (8). Constraint (9) is used to ensure that the decision variables $u_{ijt't}, z_{ijt't}$ and v_{ti} are nonnegative integer numbers.

Table 1
Notation.

Sets	
$\mathscr{I}$	Set of metro terminals, $\mathscr{I}:\{i\vert 1\leq i\leq I\vert i\in Z\}$
$\mathscr{S}$	Set of the number of carriages, $\mathscr{S}:\{s\vert 1\leq s\leq S\vert s\in Z\}$
$\mathscr{T}$	Set of time slots, $\mathscr{T}:\{t\vert 1\leq t\leq T\vert t\in Z\}$
$\mathscr{I}_i^+$	Set of metro terminals, $\mathscr{I}_i^+:\{j\vert i+1\leq j\leq I\vert j\in Z\},\forall i\in\mathscr{I}\backslash\{I\}$
$\mathscr{I}_i^-$	Set of metro terminals, $\mathscr{I}_i^-:\{j\vert 1\leq j\leq i-1\vert j\in Z\},\forall i\in\mathscr{I}\backslash\{1\}$
Parameters	
i,j	Index of metro terminals, $i,j\in\mathscr{I}$
s	Index of the number of units for a metro fleet, $s\in\mathscr{S}$
c	Capacity of one single unit
δ	Length of one-time slot
h	Minimum design headway for safe operation
p_{ijt}^{Ave}	Passengers on an average boarding from terminal i and heading to terminal j with departure time t, which are designed to arrive at time $[t-1,t]$, $i,j\in\mathscr{I}$, $t\in\mathscr{T}$
p_{ijt}	Actual passengers boarding from terminal i and alighting to terminal j with departure time t, which are designed to arrive at time $[t-1,t]$, $i,j\in\mathscr{I}$, $t\in\mathscr{T}$
d_i	Distance from terminal 0 to terminal i, $i\in\mathscr{I}$
v	Average vehicle speed, km/min
C_{op}	Average metro vehicle operation cost per vehicle
C_{s_wind}	Average metro vehicle resistance cost for vehicle fleet with s carriages per km
C_{s_GHG}	Monetary global warming impact for vehicle fleet with s carriages, \$
C_{time}	Average passenger time cost, \$/min
ΔT_i	Travel time from the first terminal to terminal i, $i\in\mathscr{I}$
Variables	
x_{tis}	Binary variables, $x_{tis}=1$ if the metro fleet with departure timed index t (departure time from first terminal at time t) is dispatched from metro terminal i with s vehicles, $x_{nit}=0$ otherwise, $t\in\mathscr{T}$, $i\in\mathscr{I}$, $s\in\mathscr{S}$
y_t	Binary variables, $t=1$ if there is a vehicle departure from the first metro terminal at time t, otherwise $t=0$, $t\in\mathscr{T}$.
w_{tis}	Binary variables, $w_{tis}=1$ if $x_{tis}y_t=1$
$z_{ijt't}$	Integer variable, the number of passengers boarding at metro terminal i and alighting to terminal j at time slot $[t'-1,t']$ and waiting for the train dispatched at time t, $t,t'\in\mathscr{T}$, $i,j\in\mathscr{I}$.
$u_{ijt't}$	Integer variable, the number of passengers arriving at metro terminal i and alighting to terminal j at time slot $[t'-1,t']$, and waiting for the subway train dispatched at time t, $t,t'\in\mathscr{T}$, $i,j\in\mathscr{I}$.
v_{ti}	Integer variable, passenger volume leaving from terminal i by the subway train departing at time t. $t\in\mathscr{T},i\in\mathscr{I}$.

3.1.4. Objective function

$$\min_{x_{tis},y_t,z_{ijt't},u_{ijt't},v_{ti}}\sum_{i\in\mathscr{I},t\in\mathscr{T},s\in\mathscr{S}}\left(C_{\mathrm{op}}+C_{s\_\mathrm{wind}}+C_{s\_\mathrm{GHG}}\right)d_{i,i+1}x_{tis}y_t+\sum_{i,j,t',t}C_{\mathrm{time}}u_{ijt't}(t+\Delta t_i-t')\delta \tag{13}$$

The objective function proposes to reduce the overall cost and provide the most efficient way to operate the metro system, considering factors, such as the amount of time needed for each dispatch and the total number of carriages present at each terminal. The total cost has two main components: the costs consumed by metro trains and the costs incurred by waiting passengers. The costs consumed by metro trains, the operating cost, are calculated based on the distance the metro carriage travels with a specific carriage number. It combines the basic metro vehicle operation cost, metro vehicle energy consumption cost to overcome wind resistance and the monetary global warming impact for the vehicle fleet. The costs incurred by waiting passengers, the waiting cost, are proportional to the passenger waiting time.

3.2. Revised formulation

The original formulation assumes that the function (13) and all the constraints, except for Constraints (3) and (7), are linear. In Constraint (3), there is a bilinear term that involves multiplying two choice variables together. We linearize Constraint (3) with an equivalence mathematical transformation, which can reach an exact result without any approximation gap. Then, the revised formulation can make the model more straightforward and make it possible to find a solution using one of the many available commercial solvers. More specifically, Constraint (3) is linearized as (14)–(16), which are as follows:

$$u_{ijt't}\leq My_t, i<j\in\mathscr{I},1\leq t'\leq T \tag{14}$$

$$u_{ijt't}\leq z_{ijt't}, i<j\in\mathscr{I},1\leq t'\leq T \tag{15}$$

$$u_{ijt't}\geq z_{ijt't}-M(1-y_t), i<j\in\mathscr{I},1\leq t'\leq T \tag{16}$$

where M is a large positive given number in this inequality.

Similarly, the bilinear term $x_{tis}y_t$ in both Constraint (7) and in function (13) should also be linearized. For ease of expression, $w_{tis}=x_{tis}y_t$ is introduced as an auxiliary variable. Considering that both x_{tis} and y_t are binary variables, w_{tis} can be linearized by Constraints (17)–(19).

$$w_{tis}\leq x_{tis}, t\in T, i\in I, s\in S \tag{17}$$

$$w_{tis}\leq y_t, t\in T, i\in I, s\in S \tag{18}$$

$$w_{tis}\geq x_{tis}+y_t-1, t\in T, i\in I, s\in S \tag{19}$$

Thus, we replace Constraint (7) with the following Constraint (20).

$$v_{ti}\leq\sum_{s\in\mathscr{S}}w_{tis}cs, t\in\mathscr{T}, i\in\mathscr{I} \tag{20}$$

$p_{ijt'}$ in Constraints (4) and (5) is a random variable subject to a Poisson distribution. To ensure that Constraints (4) and (5) are not violated in most uncertainty scenarios, we introduce the auxiliary variable $\overline{p_{ijt'}}$, which satisfies the chance constraint (21).

$$\Pr\left\{p_{ijt'}-\overline{p_{ijt'}}<0\right\}\geq 1-\varepsilon, t\in\mathscr{T}, i,j\in\mathscr{I} \tag{21}$$

where ε denotes the acceptable error.

Then, Constraints (4) and (5) can be replaced by Constraints (22) and (23).

$$z_{ijt't}=\overline{p_{ijt'}}-\sum\nolimits_{t''=\max\{1,t'-\Delta T_i\}}^{t-1}u_{ijt't''},\quad \begin{array}{c}1\leq i<I,\\ i<j\leq I,\\ 1\leq t'\leq T,\\ 1\leq t\leq T,\\ t+\Delta T_i>t'\end{array} \tag{22}$$

$$\sum_{1\leq t\leq T}u_{ijt't}=\overline{p_{ijt'}}, i,j\in\mathscr{I}, 1\leq t'\leq T \tag{23}$$

Clearly, the objective function can only take on a minimum value if $\overline{p_{ijt'}}$ takes on a minimum value. When the distribution of $p_{ijt'}$ and the value of ε are known, $\overline{p_{ijt'}}$ can be treated as a constant. See Section 3.3 for the calculation of $\overline{p_{ijt'}}$. Consequently, the researched problem is recast as a linear problem, as shown in the following function (24).

$$\begin{array}{c}\min\limits_{x_{tis},y_t,z_{ijt't},w_{tis},u_{ijt't},v_{ti}}\sum\limits_{i\in\mathscr{I},t\in\mathscr{T},s\in\mathscr{S}}\left(C_{\mathrm{op}}+C_{s\_\mathrm{wind}}+C_{s\_\mathrm{GHG}}\right)d_{i,i+1}w_{tis}+\sum\limits_{i,j,t',t}C_{\mathrm{time}}u_{ijt't}(t+\Delta t_i-t')\delta\\ \text{s.t.}(1),(2),(6),(14)-(23)\end{array} \tag{24}$$

3.3. Probability distribution of the number of passengers

For any passengers with a given origin and destination, terminals i and j, respectively, there is a departure time t, and p'_{ijt} can be formulated by a random variable with a Poisson distribution as follows.

$$\Pr\{p_{ijt'}=k\}=\frac{\left(p_{ijt}^{\mathrm{Ave}}\right)^k}{k!}e^{p_{ijt}^{\mathrm{Ave}}}, k=1,2,\cdots,\infty, t\in T, i,j\in I \tag{25}$$

where p_{ijt}^{Ave} denotes the average number of passengers who board metro terminal i that would head toward metro terminal j with departure time t and are designed to arrive at time $[t-1,t]$, which can be obtained from historical data.

In this case, we can find the minimum $\overline{p_{ijt'}}$ subjected to Constraint (21) by solving problem (26):

$$\begin{aligned}&\min k\\ \text{s.t.} &\sum_{h=[0,k]}\Pr\{p_{ijt'}=k\}\geq 1-\varepsilon\end{aligned} \tag{26}$$

For a given p_{ijt}^{Ave}, the optimum solution of (26) is a fixed value. In this case, $\overline{p_{ijt'}}$ can be regarded as a constant while solving (24).

4. Case study

4.1. Parameterization and implementation

To demonstrate the efficiency of the proposed model and the effectiveness of the proposed metro scheduling strategy, this section includes study cases utilizing actual passenger data. To resolve the problem posed by the proposed model, we use the most recent version of the Gurobi solver in this section. We conducted the simulation experiments on a laptop computer. This computer comes with an Intel Core i7-10130 processor operating at 2.7 GHz with 16.00 gigabytes of memory. We used the Win11 operating system. The simulation software chosen is MATLAB 2022a.

The data obtained from Shenzhen Metro Line No. 4 were chosen for numerical tests, as shown in Fig. 4, to simulate the effect of the proposed method in real world operation. Shenzhen Metro Line 4 is 31.3 km long, with 15 terminals, including 12 underground terminals, 1 above-ground terminal and 3 elevated terminals. The trains are designed to run at 1.33 km/min and use 6 carriages of A-type metro trains. The data are based on the passenger flows from the Shenzhen metro system smart card data on Oct. 9, 2020.

15 metro terminals were chosen from the current metro line to accommodate the passenger flow requirement in October 2020 based on the data collected from smart cards. The data on passenger demand that were utilized in the case study were collected on October 9, 2020. Fig. 5 shows the average passenger demand at each terminal. Passenger demand for service varies noticeably throughout a variety of time periods; hence, this metro line is an excellent candidate for serving as a testbed for the proposed operational paradigm.

The default parameter values are listed in Table 2. Some parameter values vary due to temporal and geographical factors; thus, we selected the values of the parameters according to the operation characteristics based on Shenzhen Metro Line 4.

4.2. Cost comparisons

Using the aforementioned data and parameter settings as input, we employed Gurobi to solve the proposed model, as shown in Table 2. The average CPU running time of this model was 3.33 min. We compared the

Fig. 4. Shenzhen Metro Line 4 in 2020.

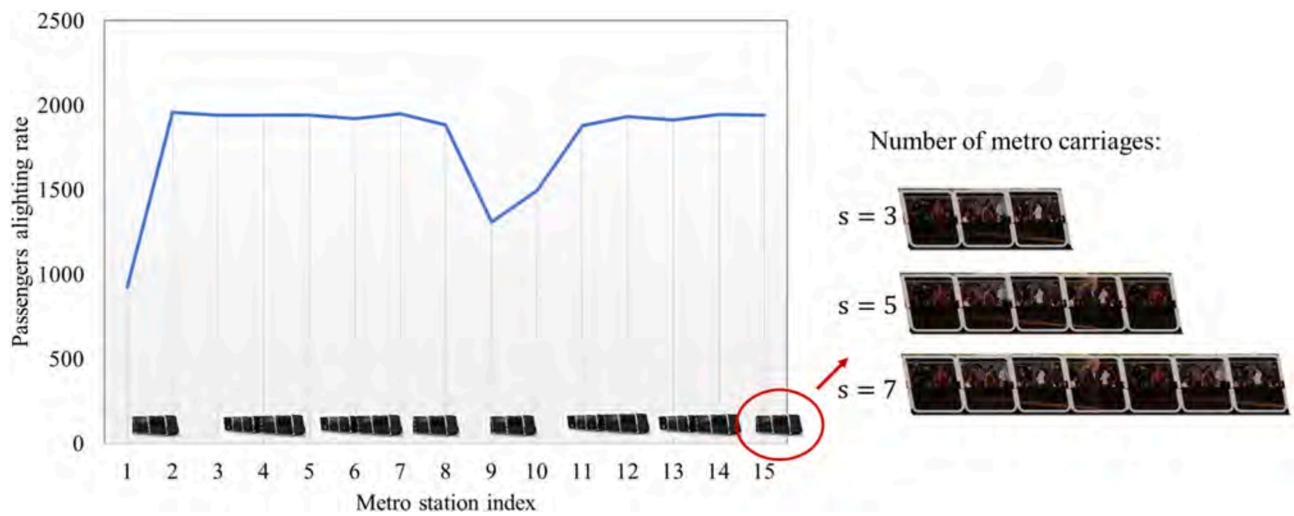

Fig. 5. Illustrative example.

Table 2
Parameter settings.

Parameter	Value	Unit	Parameter	Value	Unit
I	15 (Section 4.2&4.3) and 10 (section 4.4)	–	C_{s_wind}	[1,1.9,2.3.2.7,2.9,3]	\$
S	6	–	C_{GHG}	4.17	\$
c	350–700*	people	C_{time}	0.33	\$/min
δ	1	min	d_i	[0 2 1.3 1.6 2.8 3.8 2.6 4.8 5.3 3.3 3 1.3 2.7 1.4]	km
h	1	min	v	1.33	km/min
C_{op}	2	\$	ΔT_i	Distance/v	km

Note: Shenzhen Metro Line No. 4 has a seating capacity of 54, and according to its report, it can accommodate 6 to 12 times the number of standing people during peak hours, that is, approximately 350–700 people. Data source: MTR Shenzhen, http://www.mtrsz.com.cn/chi/.

Table 3
Result of the proposed MT system compared to the benchmark system.

	Total cost	Operation cost	Cost for overcoming wind resistance	GHG cost	Waiting time cost	Average number of carriages	Average headway
MT system	18186.03	2979.20	1765.44	1294.09	12147.30	1.21	2.07
Benchmark system	24602.71	1915.20	2872.80	3993.19	15821.52	6.00	3.22
Saving percentage	26.08 %	−55.56 %	38.55 %	67.59 %	23.22 %	79.76 %	35.71 %

Note: The benchmark system is established according to the existing Shenzhen Metro Line 4 with a capacity of 6 carriages.

MT system with the system that was already in place so that we could determine whether the proposed method was useful. The capacity of the benchmark system is determined to be six carriages based on the currently operating Line 4 of the Shenzhen Metro.

With the optimal configuration, the cost of both types totals 18186.03 dollars, whereas that of the existing system is 24602.71 dollars, as shown in Table 3. This means that the optimized MT system saves 26.08 % of the total cost. The cost reduction is modest since we set the 99 % chance constraints with a high level of safety threshold. These chance-constrained robust optimization results will be discussed in Section 4.3.

The MT system has a nearly 70 % reduction in cost and decreased GHG emissions, which profoundly verifies the outstanding performance of the MT system in providing environmentally friendly operation strategies. Additionally, the cost for overcoming wind resistance has a sharp decrease of 38.55 %, which further proves the economical savings in the MT system. Similarly, the wait time cost decreased as well. Since an increasing number of passengers focus on their trip experience, researchers have found that the most important way to increase passenger satisfaction is to decrease their travel time (Bliemer et al., 2017; Ezaki et al., 2022; Sánchez et al., 2021). In the proposed system, we found a 23.22 % reduction in wait time cost, which can provide better service than the existing system. The average number of carriages and average headway were reduced by 79.76 % and 35.71 %, respectively. The operation cost, which includes the metro carriage depreciation cost and operational economic cost, is linearly related to the number of carriages used as well as their service distance. The operational cost of the optimized MT system is increased because the MT system uses a larger number of carriages over the entire service time horizon than the existing system.

4.3. Monte Carlo analysis

The chance-constrained method of optimization programming used in this study is a process for working with random parameters within a problem while guaranteeing a certain performance (Margellos et al., 2014). The constraint is considered to satisfy the system standby constraint at a certain confidence level (i.e., 99 % in this study) to ensure the reliability of system operation. To satisfy all constraints in most scenarios, the optimization results appear relatively conservative. Specifically, the optimization results are not optimal in the scenarios that are less extreme. (Küçükyavuz and Jiang, 2022). Monte Carlo

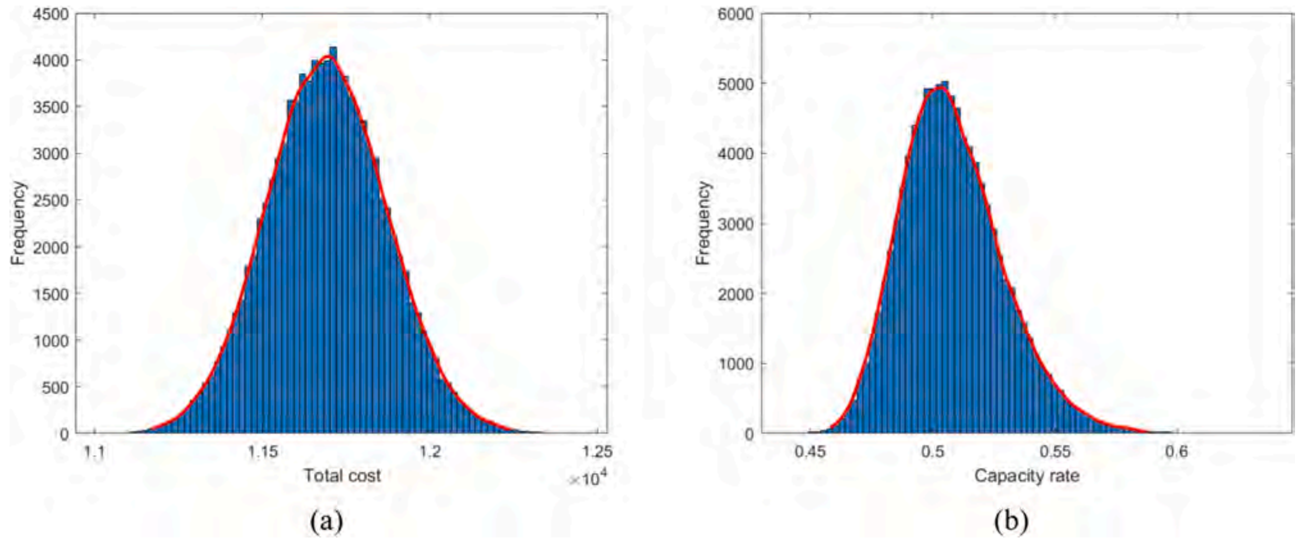

Fig. 6. Monte Carlo analysis result. (a) frequency distribution for total cost; (b) frequency distribution for MT carriage capacity.

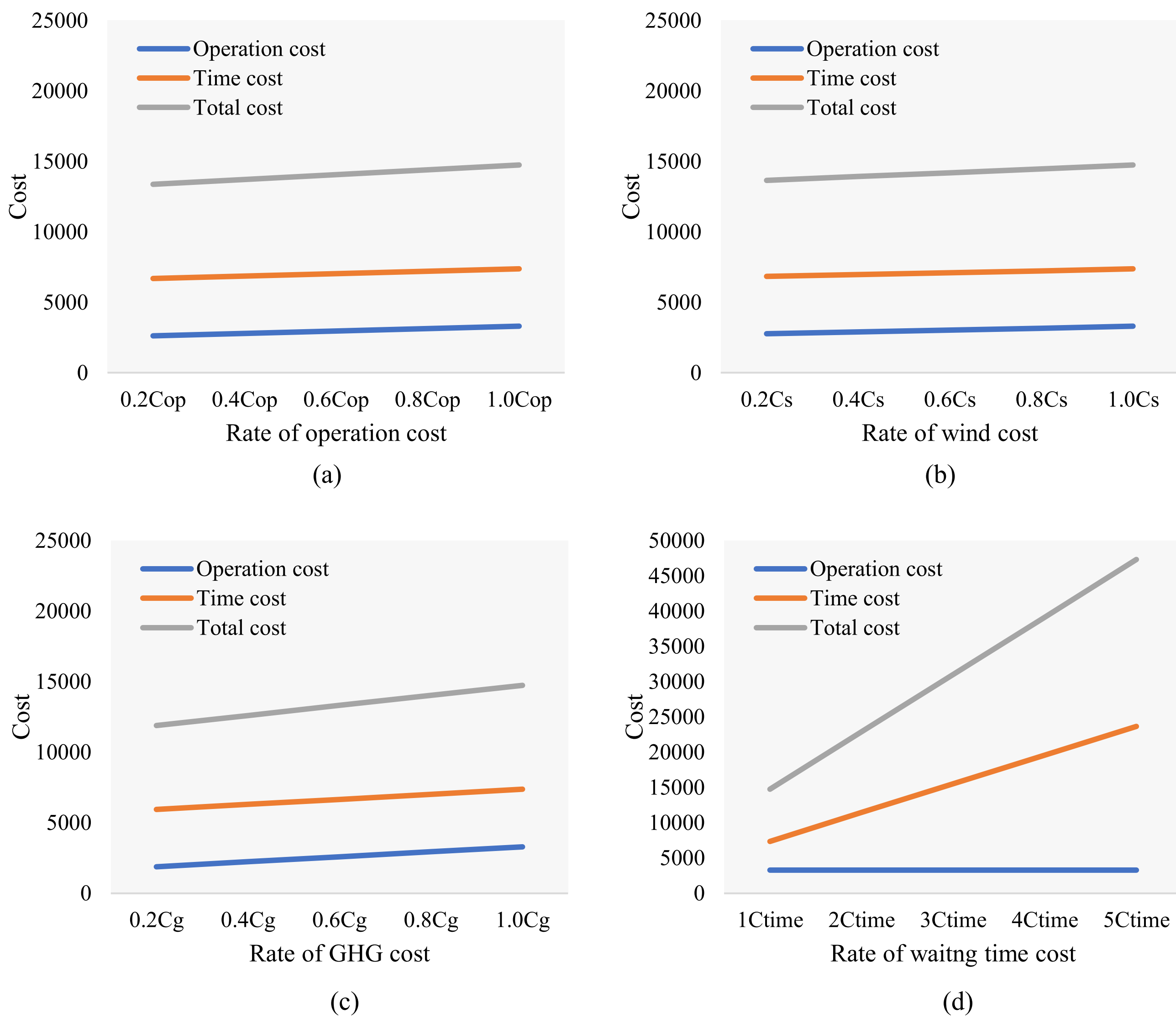

Fig. 7. Performance of the three costs with varying parameter inputs.

simulations were performed to verify the effect of the optimization results under different scenarios. A total of 100,000 scenarios are generated to approximate the distribution with a set of outcomes, i.e., the total cost and carriage capacity rate, as shown in Fig. 6(a) and (b), respectively. Thus, the capacity rate is approximately half of the designed capacity, and the total cost reduction is not considerably high in Table 3. The capacity rates in 100,000 scenarios are shown in Fig. 6(b), which indicates that the MT system can reduce the severity of constraint violations effectively under different scenarios with passenger arrival time uncertainties.

4.4. Sensitivity analysis

A sensitivity analysis is carried out on the various input parameters to determine whether the proposed method is still capable of achieving the required performance level, thus helping to further investigate the performance and applicability of the proposed model. Here, we selected the operation cost rate, wind cost rate, GHG emission cost rate and wait time cost rate. To further explore the optimization performance with varying parameter values, we propose a more typical ten-terminal numerical example in this section.

Fig. 7 shows the sensitivity analysis with different input parameter values. In Fig. 7(a), the three lines show the trends for the operation cost (blue line), time cost (orange line) and total cost (gray line). The total cost increased with an increasing operation cost. Both the wait time cost and operation cost share the same trend. Fig. 7(b) shows the performance of the wind cost, and this cost component is most closely related to the vehicle motion techniques. It slightly affects the value of the total cost compared with the other cost components, e.g., wait time cost and operation cost. Fig. 7(c) shows the performance of the three costs with varying GHG cost rates. This cost rate reflects the environmental value of society, which can become increasingly important with increasing attention to environmental protection. Fig. 7(d) compares the three costs with the wait time cost rate. The wait time cost rate reflects the time value of passengers, which can be an important part of total cost competitiveness.

5. Conclusion

This paper focused on the challenging asymmetric distribution of the passenger demand problem of metro systems and proposed a modular transit technology-based nonlinear programming model to weight the value of train power energy, greenhouse gas emissions, wind resistance, and operational economics to optimize the total system cost. In the model, the MT system allows the metro fleet to be disassembled and assembled in identical carriages dynamically at metro terminals, bringing new perspectives to the problem. Since nonlinear programming fails to provide an exact solution, we rigorously formulated the problem based on a series of linearization operations.

We illustrate the practicability of the mathematical model by study cases. We gather real world data from the Shenzhen Metro and validate the efficiency of the proposed model in terms of its economical, low-carbon, and environmental effects. The result shows that the total cost of the MT system can be 26.08 % lower than that of the existing system. The resiliency of the proposed model under a variety of parameter configurations is examined to test an additional parameter value trend.

The metro system is a perfect public transport system for modular transit. The carriages are easier to operate, composing and decomposing under the organization of the modular operation concept. However, this organization process will also encounter many challenges. Since the length of metro platform is fixed, the passenger travel guidance on the platform must be adjustable with the change of the metro train carriages, which will be very interesting research in future modular transportation system modeling, which will bring more new opportunities and challenges to the future research work. Moreover, this work can be extended in additional directions in the future. First, transportation electrification can provide more choices in public transit systems, which can bring additional challenges, e.g., vehicle charging and parking (Eliasson, 2021; Kopplin et al., 2021; Yagcitekin and Uzunoglu, 2016), battery degradation and replacement (Pelletier et al., 2017; Yang et al., 2018; Zhang et al., 2021), and charging facility options and locations (Agrawal et al., 2016; Erdelic et al., 2019; Jang, 2018). Second, connected and autonomous technologies in transportation will create a complete industrial revolution (Li et al., 2022; Peng et al., 2021; J. Zhu et al., 2022), which can be a good opportunity for modular vehicles to be used based on a connected and autonomous environment, leading to more joint optimization problems.

Declaration of Competing Interest

The 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.

Data availability

Data will be made available on request.

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