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香港旅遊巴士的上落客管理及泊車位供應

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PUBLIC POLICY RESEARCH FUNDING SCHEME

Final Report

Regulating Tourist Coach Parking in Hong Kong: Curbside Management and Carpark Provision

香港旅遊巴士的上落客管理及泊車位供應

Project No. 2022.A7.024.22B

Report by

Research Team

Smart City Lab

Department of Civil and Environmental Engineering

The Hong Kong University of Science and Technology

Nov 2024

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Executive Summary

Tourism is a pillar industry in Hong Kong. Before the COVID-19 pandemic, the tourist industry accounted for 4.5% of Hong Kong's GDP and 6.6% of the total employment. However, despite the economic benefits, it also brought an overwhelming number of tourists from mainland China. This placed heavy burdens on local residents, who complained about overcrowded shopping malls, long queues at restaurants, and congested streets caused by large numbers of tourist coaches. Among a multiplicity of issues brought about by tourism, transport-related ones associated with tourist coach parking are among the acutest. Tourist coaches frequently use curbside spaces for passenger pickup and drop-off, which aggravates traffic obstruction and disturbs pedestrians. They also regularly park illegally after passengers alight for activities, which occupies road spaces and compromises road safety. The chaotic parking activities of tourist coaches not only disrupt traffic on already-congested roads, but also exacerbate the fraught tension between mainland visitors and Hong Kong residents.

This project examines public policies aimed at regulating tourist coach parking to improve traffic conditions. We have developed a comprehensive regulatory framework addressing two facets of coach parking: (a) short-term curbside parking and (b) medium-term on-street/off-street parking. The research was structured into two parts. The first part centers on short-term curbside parking, primarily for passenger pickup and drop-off. We gathered data to calibrate a network equilibrium model for both Tsim Sha Tsui and To Kwa Wan. This model captures the movements of tourist coaches and the general traffic flow, as well as their interactions, particularly the frequent stopping of coaches at designated pickup/drop-off points. Utilizing this model, we explored the optimal placement of pickup/drop-off points and areas with no-stopping restrictions to satisfy the mobility needs of tourists while minimizing disruptions to ongoing traffic. The second part of the project focuses on hourly coach parking while passengers engage in dining, shopping, and other activities. We collected data to calibrate a spatial equilibrium model for Kowloon, which delineates the movement of coaches across different zones and the search-for-parking traffic within each zone. Using this model, we analyzed the optimal parking provision strategies that efficiently allocate parking spaces to significantly reduce traffic congestion.

In the first part of this project, we calibrated the proposed model for Tsim Sha Tsui and To Kwa Wan, and solved a bilevel mixed-integer nonlinear program to determine the optimal no-stopping restrictions and allowable pickup and drop-off locations for tourist coaches in these two areas. Our numerical results indicate that the strategic establishment of no-stopping zones and designated pickup and drop-off points resulted in a total travel time reduction of 12.1% in Tsim Sha Tsui and 17.3% in To Kwa Wan, respectively. In the second part of the project, we addressed a bilevel optimization problem with an equilibrium constraint to derive

the optimal allocation of parking spaces between private vehicles and tourist coaches. Compared to the status quo, our recommended parking space allocations led to a 4.2% reduction in cruising time for private cars and a 23.3% reduction for tourist coaches, contributing to an overall decrease in cruising time of 7.8% across the entire network.

Overall, the two parts of this project form an integrated framework that addresses the parking chaos of tourist coaches in Hong Kong. This will be of paramount importance to reducing traffic congestion, reviving economic growth, and restoring social cohesion in the post-COVID-19 era.

Summary of Policy Implications and Recommendations

The major deliverables of this project are two models that enable the government to make evidence-based policies to mitigate traffic congestion caused by tourist coaches. The first model is a bilevel mixed-integer optimization framework that determines the optimal setup of no-stopping restriction zones and allowable pickup and drop-off locations across the transportation network. The inputs for this model include the traffic flows of private vehicles and tourist coaches, as well as the congestion characteristics of each road segment within the considered area. The output of the model consists of policy recommendations. This model has been validated in two study areas, Tsim Sha Tsui and To Kwa Wan, with results demonstrating a 12%-17% improvement in traffic flows following the implementation of the proposed policies in these areas. The second model is a bilevel optimization framework with equilibrium constraints, taking into account the traffic flows of private vehicles and tourist coaches, along with the congestion characteristics of each city zone. The outputs are policy recommendations that detail the optimal allocation of parking spaces between private vehicles and tourist coaches. This model has been validated in a case study covering the entire Kowloon area, showing that the proposed policy can significantly reduce cruising traffic across the overall transportation network.

The above results suggest the necessity for the Hong Kong government to implement a variety of policies to address the traffic congestion cause by tourist coaches. These policy recommendations are summarized below:

- *Strategic Implementation of No-Stopping Restrictions (NSRs)*. The government should consider implementing no-stopping restrictions and designating pickup and drop-off points in tourism hotspots to direct tourist coach drivers to specific locations for loading and unloading tourists. This strategy will help avoid unnecessary cruising and traffic obstructions. Importantly, the establishment of no-stopping zones should rely on scientific analysis, taking into account the traffic flows of private vehicles and tourist coaches, link capacity and performance, as well as route choices across the transportation network. We recommend that the government apply the mathematical framework developed by our project to determine optimal strategies for the placement of no-stopping restrictions and designated pickup and drop-off locations to mitigate congestion. To ensure effective enforcement of these no-stopping restrictions, we also recommend the government to implement clear and comprehensive signage for tourist coaches, deploy real-time monitoring systems such as video cameras to deter and detect parking violations, and increase police patrols in tourist hotspots and areas with no-stopping restrictions to ensure strict adherence to the law.
- *Optimizing Parking Space Allocation between Tourist Coaches and Private Vehicles*. We

recommend that the government reconsider the allocation of existing parking spaces between private vehicles and tourist coaches. More importantly, such allocation decisions should be made based on scientific evidences. In this project, we developed a bilinear optimization framework with equilibrium constraints to derive optimal parking space allocation strategies for both tourist coaches and private vehicles. This model provides strategies for optimal parking space provision based on various factors, including the spatial distribution of travel demand for private vehicles, the modal split between private vehicles and public transport, and zonal-level congestion characteristics. We advise relevant agencies to utilize the proposed mathematical model to guide the planning of parking spaces. The model delivers evidence-based policy guidance for the optimal use of land spaces to enhance traffic performance and mitigate the negative externalities caused by tourist coaches.

- *Jointly Considering Provision of Parking Space and the Provision of Public Transport Services*. We recommend that when the government formulates policies to determine parking provisions for tourist coaches and private vehicles, it should also consider how these provisions influence the transportation choices of private vehicle passengers. Our research has shown that optimal parking allocations for tourist coaches and private vehicles are not solely based on their respective shares of traffic flow. Instead, parking spaces allocated to tourist coaches typically surpass their proportion of overall traffic in each city zone, thereby encouraging some private vehicle users to switch to public transit. This holistic approach to policy-making not only addresses parking needs but also promotes more sustainable transportation choices, benefiting traffic flow and environmental quality.
- *Supporting Data Collection and Development of Information Technology Systems for Real-time Congestion Management*. We recommend that the government support enhanced data collection, specifically targeting the real-time locations of tourist coaches. This information is crucial not only for developing long-term optimal parking strategies but also for enabling more adaptable transportation policies regarding no-stopping restrictions and the selection of permissible pickup and drop-off locations. Such dynamic and advanced management of tourism traffic will significantly improve overall traffic performance across the transportation network. Furthermore, we advocate for the development of information and technology systems designed to proactively manage the travel choices of tourists and tourist coaches to mitigate congestion. Currently, the decision-making process for allocating parking spaces, establishing no-stopping restrictions, and selecting allowable pickup and drop-off locations often lacks real-time data integration. The proposed information and technology system should be able to offer personalized recommendations to individual tourist coach drivers by planning their

daily itineraries. This will help prevent congestion caused by large groups converging on the same location simultaneously. Implementing such a system will shift traditional tourism management strategies from a passive resource allocation based on predetermined demand to a proactive approach where demand is actively shaped by information and technology systems.

In summary, the recommendations outlined in this report provide a comprehensive strategy for the Hong Kong government to address the challenges of traffic congestion caused by tourist coaches. The proposed policies are expected to lead to more scientifically-supported management strategies for tourist traffic, ultimately enhancing traffic performance throughout the city and reducing the environmental impact of congestion.

行政摘要

旅遊業是香港的支柱產業，在新冠疫情之前，每年為香港貢獻高達 4.5%的 GDP 和 6.6%的工作崗位。然而自 2003 年以來，大量大陸旅客湧入香港，影響了社區的購物、用餐、交通與環境，加重了本地居民的生活負擔。在旅遊業帶來的諸多問題中，與旅遊巴士相關的交通問題最為嚴重。旅遊巴士湧入窄小的城區街道，佔用了大量道路空間。同時，旅遊巴士在旅遊熱點區域違例泊車和違例停車上落客，極易造成交通阻塞和意外。以上問題不僅給香港居民的日常出行帶來了極大不便，也同時加劇了大陸旅客和香港居民之間的緊張關係。

此項目考察旨在調節旅遊巴士停車的公共政策，以改善交通狀況。我們已經開發了一套全面的監管框架，涵蓋巴士停車的兩個方面：（a）短期路邊停車和（b）中期路面/場外停車。研究分為兩部分。第一部分集中於短期路邊停車，主要用於乘客上下車。我們收集了數據來校準尖沙咀和土瓜灣的網絡平衡模型。此模型捕捉旅遊巴士的運動和一般交通流量，以及它們的互動，特別是巴士在指定上下車點的頻繁停靠。利用這個模型，我們探索了滿足遊客出行需求的同時，將對正在進行的交通最小化干擾的上下車點和禁停區的最佳位置。項目的第二部分關注於遊客進行用餐、購物及其他活動時的每小時巴士停車。我們收集了數據來校準涵蓋九龍各個區域的空間平衡模型，描述了巴士在不同區域的運動以及每個區域內尋找停車位的交通。使用此模型，我們分析了有效分配停車位的最佳停車供應策略，顯著減少了交通擁堵。

在這個項目的第一部分，我們為尖沙咀和土瓜灣調校了所提議的模型，並解決了一個雙層混合整數非線性程序，以確定這兩個地區旅遊巴士的最佳禁停限制和允許的上下車地點。我們的數值結果表明，設立禁停區和指定上下車點的策略導致尖沙咀和土瓜灣的總行駛時間分別減少了 12.1%和 17.3%。在項目的第二部分，我們處理了一個具有平衡限制的雙層優化問題，以推導出私家車和旅遊巴士之間停車位的最佳分配。與現狀相比，我們推薦的停車位分配導致私家車的巡航時間減少了 4.2%，旅遊巴士減少了 23.3%，對整個網絡的總巡航時間減少了 7.8%。

總體而言，這個項目的兩部分形成了一個整合框架，解決了香港旅遊巴士的停車混亂問題。這將是減少交通擁堵、恢復經濟增長和恢復後 COVID-19 時代社會凝聚力的至關重要。

政策影響和建議

此項目的主要結果是兩個模型，使政府能夠制定基於證據的政策，以減少旅遊大巴車引起的交通擁堵。第一個模型是一個雙層混合整數優化框架，用於確定交通網絡中不允許下客的限制區和允許的上下客地點的最佳設置。此模型的輸入包括私家車和旅遊大巴車的交通流量，以及所考慮區域內每個路段的擁堵特性。模型的輸出包括政策建議。此模型已在尖沙咀和土瓜灣兩個研究區域得到驗證，結果顯示在這些地區實施建議政策後，交通流量改善了 12%-17%。第二個模型是具有均衡約束的雙層優化框架，考慮了私家車和旅遊大巴車的交通流量以及每個城市區域的擁堵特性。輸出是詳細說明私家車與旅遊大巴車停車空間最佳分配的政策建議。這個模型已在涵蓋整個九龍區的案例研究中得到驗證，顯示所提政策能顯著減少整個交通網絡的巡航交通。

以上結果表明香港政府有必要實施多種政策來解決旅遊大巴車造成的交通擁堵。這些政策建議如下：

- **設置不允許下客人的限制區**。政府應考慮實施不允許下客人的限制區，並在旅遊熱點設置上下客點，引導遊覽車司機在指定地點上下旅客。這策略將有助於避免不必要的巡航和交通阻塞。重要的是，建立不停車區應依據科學分析，考慮私家車和遊覽車的交通流量、聯結容量和性能，以及交通網絡中的路線選擇。我們建議政府應用我們項目開發的數學框架，確定設置不下客限制和指定上下客地點的最佳策略，以緩解擁堵。為確保這些不下客限制的有效執行，我們還建議政府為旅遊大巴車實施清晰而全面的標誌、部署實時監控系統如視頻攝像頭以阻止和檢測違規停車，並在旅遊熱點及有不下客限制的地區增加警察巡邏，以確保嚴格遵守法律。
- **優化旅遊大巴車與私家車停車空間分配**。我們建議政府重新考慮私家車與旅遊大巴車現有停車空間的分配。更重要的是，這種分配決策應基於科學證據。在本項目中，我們開發了一個具有均衡約束的雙線性優化框架，以導出旅遊大巴車和私家車的最佳停車空間分配策略。這個模型提供了基於私家車旅行需求的空間分布、私家車與公共交通的模態分裂以及區域級擁堵特性等多種因素的最佳停車配置策略。我們建議相關機構利用所提出的數學模型指導停車空間的規劃。該模型提供了基於證據的政策指導，以最佳化土地空間使用，提高交通性能並減少旅遊大巴車造成的負外部性。
- **共同考慮停車空間和公共交通服務的提供**。我們建議政府在制定旅遊大巴車和私家車停車設施政策時，也應考慮這些設施如何影響私家車乘客的交通選擇。我們的研究顯示，旅遊大巴車和私家車的最佳停車分配不僅基於各自的交通流量份額。相反，分配給旅遊大巴車的停車空間通常超過它們在每個城市區域的總交通流量比例，從而鼓勵一些私家車使用者轉乘公共交通。這種全面的政策制定方法不僅滿足停車需求，還促進了更可持續的交通選擇，有利於交通流量和環境質量。

- **支持數據收集和信息技術系統的發展，用於實時擁堵管理**。我們建議政府支持加強數據收集，特別是針對遊覽車的實時位置信息。這些信息不僅對開發長期最佳停車策略至關重要，也有助於使有關不下客限制和允許上下客地點的選擇的交通政策更加靈活。這種動態和先進的旅遊交通管理將顯著改善整個交通網絡的交通性能。此外，我們倡導開發旨在主動管理遊客和旅遊大巴車旅行選擇的信息和技術系統，以緩解擁堵。目前，分配停車空間、建立不下客限制和選擇允許上下客地點的決策過程往往缺乏實時數據整合。所提出的信息和技術系統應能夠通過規劃其每日行程為每個旅遊大巴車司機提供個性化建議。這將有助於防止大型團體同時聚集在同一地點而引起的擁堵。實施這樣的系統將使傳統的旅遊管理策略從基於預定需求的被動資源分配轉變為基於信息和技術系統主動塑造需求的主動方式。

總之，本報告概述的建議為香港政府解決遊覽車引起的交通擁堵問題提供了一個全面策略。預期這些政策將導致更科學支持的遊客交通管理策略，最終提高整個城市的交通性能並減少擁堵的環境影響。

Chapter 1. Introduction

Tourism is a mainstay for many cities, acting as a crucial engine for their economic growth. In the context of Hong Kong, the tourism industry contributes 4.5% to the total GDP and provides nearly 260,000 jobs, equivalent to 6.6% of the total employment (Board, 2021). Despite the economic benefits, the influx of visitors exerts significant pressure on local residents, creating substantial friction between visitors and locals. Prior to the pandemic, hundreds of tour groups would descend upon Hong Kong daily during the holiday season. As these groups flocked to local restaurants, pharmacies, and jewelry stores, locals faced overcrowded shopping centers, lengthy restaurant waits, and traffic-choked roads teeming with tourist coaches (Su et al., 2018). The outbreak of COVID-19 temporarily eased these tourism-related strains, but a recurrence is anticipated as all COVID-19-prevention measures are lifted and international travel fully resumes. According to the UNWTO World Tourism Barometer (World Tourism Organization, 2023), international tourism continues to recover from the pandemic, with arrival numbers from January to July 2023 reaching 84% of pre-pandemic levels.

Among the plethora of issues stemming from tourism, transportation-related problems linked to tourist coach parking are particularly severe. Unregulated parking of tourist coaches intensifies traffic congestion and jeopardizes road safety in densely packed tourism hotspots. Due to their large size, tourist coaches occupy substantially more space than private cars and have a much greater impact on traffic congestion. To accommodate travelers, coach drivers often use curbside spaces to pick up and drop off passengers, obstructing traffic and disturbing pedestrians. Moreover, the scarcity of designated parking spaces often compels coach drivers to illegally park on street curbsides once passengers disembark, which occupies substantial road space and poses serious safety risks to other drivers. The aforementioned issues are further compounded as large coaches fill narrow streets in residential areas, creating a nuisance in communities and exacerbating tension between visitors and local residents. For instance, many tourism hotspots in Hong Kong are located in the inner streets of To Kwa Wan, Kowloon City, and Hung Hom, which are popular destinations for mainland tourist groups due to the abundance of local restaurants, pharmacies, jewelry shops, and souvenir stores in these areas. From 2017 to 2019, within the Kowloon City Police District, reports of these issues led the Hong Kong Police to issue a total of 4,192 fixed penalty notices to tourist coaches for traffic infringements (HKSAR, 2019).

These issues have spurred the government to implement various measures to regulate tourist coach parking. Using the Hong Kong Government as an example, the Transport Department has endeavored to identify suitable pick-up/drop-off points for tourist coaches in areas where traffic conditions allow and road safety is not compromised. The government has allocated

short-term tenancy parking spaces for tourist coaches and offered substantial discounts to incentivize coach drivers to park in designated areas. Currently, there are 96 on-street metered parking spaces, 110 lay-bys for pick-up or drop-off purposes, and 73 parking spaces exclusively for tourist coaches in short-term tenancy car parks in To Kwa Wan and Hung Hom (HKSAR, 2019). From 9 a.m. to 8 p.m., the parking fee in temporary car parks near tourist attractions is reduced to 6$ per half-hour to encourage tourist coaches to park off-street. Additionally, the Transport Department has established "No-stopping Restrictive Zones" in selected road segments to prohibit tourist bus activities during certain hours. To Kwa Wan and Hung Hom have been prioritized by the Police and the Transport Department to enforce against unlawful parking. The police closely monitor the situation pertaining to illegal parking and passenger pick-up/drop-off by tourist coaches in these areas and strictly enforce measures to deter illegal coach parking activities that could cause traffic congestion and endanger other road users. It's worth noting that regulating tourist coach parking is not just a local issue for Hong Kong, but a global concern in tourism hotspots of many other cities, such as London (Transport for London, 2022), Paris (Convention and Visitors Bureau, 2022), and Brussels (City of Brussels, 2022). As a result, the problem we study in this paper is pertinent to all cities with a high volume of tourist visitors.

Despite the significance of the issue, there is a lack of research focused on the provision of parking spaces for tourist coaches within bi-modal transportation networks. Addressing this gap is a complex task due to the intricate interplay that exists between parking space availability and the resulting traffic flows. Notably, the allocation of parking spaces can significantly influence the cruising-for-parking behaviors of vehicles. This, in turn, impacts vehicle accumulation in the vicinity of travelers' destinations. The traffic congestion induced by these cruising-for-parking movements affects all vehicles using the road network, including passing-by traffic as well as vehicles arriving near the destination, causing significant carbon emissions and environmental pollution. These elements also shape the route choices of tourists and local commuters alike, resulting in a complex traffic flow that intertwines on-route traffic and cruising-for-parking traffic. Adding another layer of complexity, we must also understand how the distribution of parking spaces affects all these interactions and the resulting equilibrium in the bimodal transportation network, where tourist coaches and private vehicles exhibit distinct travel patterns. Although there is a substantial body of literature on transportation network modeling and parking management, we have found that studies specifically addressing parking space provision for multi-class vehicles within a bi-modal context are lacking in the existing literature.

To address the aforementioned challenges, this project investigates public policies that regulate tourist coach parking for traffic improvement. We developed a comprehensive regulatory framework that considers two aspects of coach parking: (a) short-term curbside

parking and (b) medium-term on-street/off-street parking. The proposed research is organized into two parts. The first part will focus on short-term curbside parking for passenger pickup and drop-off. We have collected data to calibrate a network equilibrium model for Tsim Sha Tsui and To Kwa Wan, which captures the movement of tourist coaches and background traffic, as well as their interactions due to frequent stopping of coaches at designated pickup/drop-off locations. Based on this model, we investigate the optimal placement of pickup/drop-off points and no-stopping restrictive areas, so that the mobility needs of tourists can be met with minimum disruptions to traffic. The second part of the project focuses on hourly coach parking while passengers alight for dining, shopping, and other activities. A spatial equilibrium model has been calibrated for Kowloon, which characterizes the flow of coaches between zones and the cruise-for-parking traffic within each zone. Based on this model, we investigate the optimal parking provision strategies that efficiently allocate parking spaces to mitigate traffic congestion. Overall, the research objectives of this project can be summarized as follows:

(1) **Objective 1:** to develop policies that regulate the short-term curbside parking of tourist coaches. We will collect data to calibrate a link-level network equilibrium model for To Kwa Wan and Tsim Sha Tsui. The model will be used to investigate the optimal placement of pickup/drop-off points and no-stopping restrictive areas that minimizes traffic interruptions caused by tourist coaches.

(2) **Objective 2**: to develop policies that address the medium-term parking needs of tourist coaches. We will collect data to calibrate a zonal-level spatial equilibrium for Kowloon. The model will be used to investigate the optimal parking provision strategies in each district of Kowloon to reduce travel cost and mitigate traffic congestion

To achieve the first objective, we investigate how to regulate curbside pickup and drop-off from tourist coaches to balance the mobility needs of the tourists and their disruption to traffic. In particular, Task I was conducted in three phases: (1) in Phase I, we developed a network equilibrium model to characterize the flow of tourist coaches, private cars, and their interactions in the transportation network; (2) in Phase II, we collected multi-source real-world data to calibrate the model parameters for a case study in To Kwa Wan and Tsim Sha Tsui; and (3) in Phase III, we used the calibrated model to investigate the optimal placement pickup/drop-off points and no-stopping restrictive zones to minimize traffic disruptions caused by tourist coaches.

To achieve the first objective, we investigated how to provide on-street and off-street parking spaces for hourly parking of tourist coaches to minimize their negative externality on traffic congestion. Task II was decomposed into three phases: (1) in Phase I, we developed a zonal-level spatial equilibrium model that captures the spatial distribution of private cars, the spatial

distribution of tourist coaches, their cruise-for-parking behaviors, and the corresponding traffic congestion; (2) in Phase II, we collected multi-source real-world data to calibrate model parameters for a case study of Kowloon; and (3) in Phase III, we investigated how the provision of parking spaces affects cruise-for-parking behaviors, and how to determine the provision and pricing of on-street and off-street parking spaces in each zone of the city to minimize overall traffic congestion.

Chapter 2. Literature Review

2.1 Curbside Pickup and Dropoff

Tourism cities face an increasing side-effect of tourist coaches illegally stopping at the curbside. Regulations to alleviate the impact of tourist coaches on traffic congestion can be applied by designating parts of curbside lanes as parking segments, while others are not permitted for parking. When a curbside lane segment is allowed for tourist coaches to park, the capacity of that road decreases due to the occupied lane. Therefore, regulating road rights for tourist coaches alters travel behaviors and results in a new traffic equilibrium. Essentially, redesigning road rights involves shrinking road capacity by using lanes for parking tourist coaches to optimize the traffic system.

This problem can be classified as a network design problem (NDP). The NDP involves the optimal allocation of existing road lanes to be either permitted or not permitted for tourist coaches to park, aiming to optimize network performance in a user equilibrium (UE) manner. In the literature, this problem is addressed as a bi-level problem where the upper level decides road expansion or shrinkage (as in this report), while the lower level reaches UE under given upper decision variables to optimize the system. Due to its intrinsic complexity, the NDP is recognized as an NP-hard problem, even in the continuous network design problem (CNDP) case.

The NDP can be categorized into the continuous network design problem (CNDP) (see, e.g., (Abdulaal and LeBlanc, 1979), (Gao et al., 2007), (Wang et al., 2014), (Sun, 2016)), where link capacities are assumed as continuous variables, and the discrete network design problem (DNDP), where decision variables can only take a set of given numbers, as well as the mixed network design problem (MNDP) (see (Yang and H. Bell, 1998), (Luathep et al., 2011)), which combines CNDP and DNDP. From the aspects of network features and functions, the NDP can also be categorized into the road network design problem (RNDP) and the service network design problem (SNDP). The RNDP determines the topologies, capacities, or both of the urban network under different criteria, as seen in (Cantarella and Vitetta, 2006), (Szeto et al., 2015), (Hosseininasab and Shetab-Boushehri, 2015), (Mahmoudi et al., 2019). The SNDP designs the transit network, including station locations, frequencies, prices, and more, to serve users' demand between specific origin-destination (OD) pairs ((Fan and Machemehl, 2006), (An and Lo, 2016), (Liu and Zhou, 2016), liang2019(Liang et al., 2019)). Based on the certainty/uncertainty of demands, the NDP can be categorized into network design problems with certainty (deterministic) demand (NDP-C/D) and network design problems with uncertainty (stochastic) demand (NDP-U/S) ((Juan et al., 2012), (An and Lo, 2015), (An and Lo, 2016), (Li et al., 2021)). Additionally, recent works simultaneously considering the NDP and transit network design problem ((Zhang et al., 2014), (Brands and Van Berkum,

2014)) or its accessibility ((Di et al., 2018), (Yang et al., 2020)) are gaining traction.

The NDP is a well-studied optimization problem in transportation. The goal is to identify the optimal set of candidate links or arcs to be added to the system while accounting for users' behaviors as calibrated by a traffic equilibrium. Thus, the NDP is a hierarchical process reflecting interactions between decision-makers and users. The DNDP was introduced by (Leblanc, 1975) and formulated as a bi-level problem solved using a branch-and-bound (B&B) algorithm. Here, the upper-level variables decide how many links or arcs and capacities should be constructed, while the lower level reflects a traffic pattern responding to upper-level decisions ((Wang et al., 2013), (Szeto et al., 2015), (Chiou, 2016), (Di et al., 2018)). Due to the complexity of this bi-level formulation, many efforts have been made to solve this problem. (Poorzahedy and Turnquist, 1982) approximated the NDP's objective function and transformed the bi-level model into a single one, with similar attempts seen in ((Li et al., 2012), (Wang et al., 2013), (Farahani et al., 2013), (Liu and Zhou, 2016), (Yin et al., 2017)). The accuracy of the resulting solution depends on the degree of approximation of the original nonlinear travel time function. Nonetheless, MILP-based approximation methods allow for using existing optimization software (e.g., CPLEX solver). Combining with methods like outer approximation (Wang et al., 2015), the linearized and relaxed MILP can be used as a lower bound of the global optimum of the original problem.

Other attempts like heuristic methods based on B&B have been developed. (Farvaresh and Sepehri, 2013) provided a strict lower bound for the upper-level objective with a revised B&B algorithm, further developed by (Gokalp et al., 2021), proposing a bidirectional search heuristic with customized pruning and branching strategies exploiting specific traffic assignment properties. Additionally, a Benders decomposition method (Fontaine and Minner, 2014) was proposed for solving discrete-continuous linear bi-level problems in the NDP context. (Mohebifard and Hajbabaie, 2019) proposed a dual estimation algorithm for the MINLP to generate Benders cuts using a simulation-based approach to a signal timing optimization program. (Nieto-Isaza et al., 2022) developed an enhanced Benders decomposition to solve a two-stage stochastic program for the strategic location of mini-depots for crowdsourced last-mile delivery. (Fragkos et al., 2021) solved uncapacitated and capacitated network expansion problems using Benders decomposition and heuristic methods, respectively. Recently, supervised machine learning (SML) has been pioneering in solving bi-level models for network design and traffic assignment problems (Zaferanieh et al., 2023). Redesigning large-scale multimodal transit networks is emerging with shared autonomous mobility services (Ng et al., 2024).

Using curbside road lanes for driving lanes or parking spaces is crucial, considering the paradox between maximizing public service and minimizing traffic congestion. Curbside

lanes are valuable real estate for cities, accommodating many competing demands such as private vehicles, passenger pick-up/drop-off, freight loading/unloading, public transit stations, buses, and others (Jaller, 2021). Efficient use of curbside parking is crucial to accessibility and the local economy, whereas poor management of curbside spaces leads to increased vehicle cruising, exacerbated traffic congestion, illegal parking, and safety risks (Jaller et al., 2021). (Gu et al., 2013) developed an analytical model based on kinematic wave theory to determine the optimal placement of near-side bus stops to achieve a target level of residual car queuing. (Nourinejad et al., 2014) presented an econometric parking choice model to analyze the potential impact of truck parking policies in urban areas. (Luthy et al., 2016) investigated the types (curbside vs. bus bay) and locations of bus stops and compared the delays that cars and buses experience based on distinct types and locations of bus stops. In recent years, the emergence of ride-hailing platforms, shared mobility, and other new technologies has added complexity to managing curbside spaces (Diehl et al., 2021). This inspired new research directions addressing curbside management under new transportation environments. (Ma et al., 2018) investigated the impacts of shared and autonomous vehicles, establishing that curbside spaces could be repurposed for other uses for more extensive community benefits under high penetration of shared autonomous vehicles. (Liu et al., 2020) developed a double machine learning model to quantify how much passenger pick-ups/drop-offs from ride-hailing vehicles affect traffic flow and how to reroute ride-hailing vehicles to alternative road sections to reduce congestion. (Xiao, 2019) studied congestion mitigation strategies via the placement of pick-up/drop-off points for ride-hailing platforms during planned special events. Recently, pilot studies in San Francisco and Washington D.C. utilized new technologies to provide additional information for travelers about the availability of curbside space in real-time.

Numerous works have focused on transit priority ((Shalaby, 1999), (Yang and Huang, 2004), (Li and Ju, 2009), (Yu et al., 2015)). (Zhu et al., 2012) investigated the impact of curbside and median bus lanes on expressway traffic. (Yao et al., 2012) established a bi-level programming model to optimize the joint utilization of exclusive bus lanes and bus frequencies to minimize the total cost for travelers and transit operators. However, tourist coaches differ from transit vehicles like buses, as tourist coaches are deemed social vehicles that cannot use bus lanes. Additionally, tourists typically travel to specific destinations (e.g., tourist spots) and do not need to stop mid-journey. Because tourists are grouped for identical purposes, they have some degree of destination choice.

Distinct from the aforementioned works, the proposed research investigates regulations on curbside parking with a particular focus on tourist coaches. The curbside use pattern of tourist coaches significantly differs from that of private cars, ride-hailing vehicles, and buses. For example, tourist coaches can flexibly park a few blocks away from the target destination to

load/unload passengers and park at a farther distance when passengers alight for other activities. These differences should be explicitly considered when modeling the interactions between tourist coaches and other vehicles in determining the optimal placement of pick-up/drop-off locations and no-stop regulation zones. This study presents a novel approach to optimizing the distribution of No-Stop Regulations (NSRs) for tourist coach pick-up and drop-off activities in urban environments, with a specific focus on their interaction with private car traffic. The problem is formulated as a bi-level mixed integer optimization problem with equilibrium constraints, where the upper level represents government decision-making on NSR placement to minimize total network travel time, while the lower level models the equilibrium behavior of private cars and tourist coaches under given NSRs.

To solve this complex problem, we developed a tailored outer approximation (OA) algorithm, enhanced by several innovative techniques including linearization of the objective function and constraints, a demand-shifting procedure, and acceleration methods such as tightening the feasible region for integer variables and introducing link thresholds the pre-identification of congested and smooth links.

The proposed method was applied to a case study in the Tsim Sha Tsui district of Hong Kong, demonstrating its practical applicability. Results show a 4.6% improvement in total travel time compared to scenarios without NSRs. The algorithm exhibited rapid convergence. Comparative analysis revealed that the pre-identification of congested and smooth links significantly enhanced computational efficiency, reducing calculation time by more than a factor of 10.

2.2 Cruising for Parking

The literature frequently addresses the characterization of cruising-for-parking behaviors among travelers and assesses their impact on traffic performance (Liu, 2018). Studies indicate that over 8% of urban drivers participate in cruising for parking. This figure escalates to 30% during peak hours in central business districts, with the average search time reaching 8.1 minutes (Shoup, 2006). The externalities of cruising-for-parking contribute significantly to traffic performance, often inducing congested or severely congested traffic conditions (Arnott and Inci, 2006a). Numerous empirical and analytical studies have delved into estimating cruising-for-parking by investigating the average search distance or time and its interplay with traffic congestion (Arnott and Rowse, 1999), (Arnott and Inci, 2006a), (Anderson and De Palma, 2004), (Martens et al., 2010a), (Geroliminis, 2015a). For instance, (Arnott and Rowse, 1999) considered the search for vacant parking spaces as random events and employed the negative exponential law to estimate the search time. (Geroliminis, 2015a) formulated the parking process as a Bernoulli trial, with the success probability representing

the ratio of vacant to total parking spots.

From an economic perspective, (Arnott and Inci, 2006a) explored the interplay between cruising-for-parking and traffic congestion. They modeled parking at a steady state, considering three distinct vehicle states: (i) moving, (ii) cruising-for-parking, and (iii) parked. While their study did not account for system dynamics, it offered valuable insights into these relationships based on static stationary conditions. Recent advancements in urban network traffic flow modeling have shown promise in simulating the dynamics of traffic congestion and propagation in large-scale networks (Geroliminis and Daganzo, 2008a). (Geroliminis, 2015a) and (Liu and Geroliminis, 2016) proposed extensions of these approaches to characterize the impact of parking on traffic operations during peak hours in congested cities. (Boyles et al., 2015) integrated cruising-for-parking into static and dynamic traffic assignment models by refining cost functions. (Martens et al., 2010a) and (Zhao et al., 2021)introduced agent-based parking simulation models to illustrate the search process. (Cao and Menendez, 2015a) validated a macroscopic system dynamic model to capture the interaction between cruising-for-parking and traffic performance. (Zhao et al., 2021) proposed a model predictive control approach for parking and congestion control in an area of mixed CVs and AVs.

Aside from the aforementioned works, multiple strategies have been explored in the literature to mitigate the traffic congestion caused by cruising-for-parking behaviors in urban areas. These strategies have examined various parking pricing schemes and strategies for managing parking demand, such as curbside parking time limits (Arnott and Inci, 2006a), parking reservations (Boyles et al., 2015), and tradable parking permits (Zhang et al., 2011). Parking pricing, combined with other demand management strategies, can reduce cruising-for-parking traffic through modal shifts (Anderson and De Palma, 2004), (Qian and Rajagopal, 2015), (Zheng and Geroliminis, 2016), (Gu et al., 2020). Advances in sensing and communication technologies have facilitated the development of Parking Guidance and Information (PGI) systems by several metropolitan traffic authorities to enhance parking operations (Idris and Mohd, 2009). A host of smartphone-based parking applications leverage location-based services to enhance parking spot allocation (news.gov.hk, 2013), (Chen et al., 2019), (Zhao et al., 2021). Shared parking mechanisms have been proposed to efficiently utilize temporarily vacant private parking resources in residential areas, catering to public demand during daytime given the scarcity of parking spaces in urban areas (Shao et al., 2016). (Geroliminis, 2015b) demonstrated that perimeter control can significantly reduce delays if cruising-for-parking is not intense and trips are not primarily originating from downtown areas. However, while these studies mainly address parking issues related to private cars, there is a noticeable gap in research specifically addressing the parking problem for multi-class vehicles in bi-modal transportation networks.

2.3 Modeling Congestion

The macroscopic fundamental diagram (MFD) offers an accurate model for establishing a physical relationship between the (multimodal) network topology and the average network journey time under varying demand conditions (Daganzo and Geroliminis, 2008), (Leclercq et al., 2014). The idea of using the MFD for car-only urban networks was initially proposed by (Godfrey, 1969) and was re-initiated later in (Mahmassani et al., 1987) and (Daganzo, 2007). With substantial empirical evidence supporting the existence of the MFD on a large scale (Loder et al., 2019), its practical utilization in policymaking becomes feasible.

Several studies have underscored the role of spatial congestion distribution in influencing the shape and scatter of the MFD, observing that areas with lower spatial heterogeneity typically exhibit higher flows (Geroliminis and Sun, 2011), (Mahmassani et al., 2013), (Knoop et al., 2013). In parallel, analytical theories have been formulated to characterize the shape of the MFD, taking into account network and intersection parameters. Both homogeneous and heterogeneous network topologies have been analyzed using variational theory (Geroliminis and Daganzo, 2008b), (Geroliminis and Boyacı, 2012), (Leclercq and Geroliminis, 2013). Furthermore, the properties of a well-formulated MFD, including its stability and scatter phenomena, have been scrutinized through a plethora of simulation studies and experimental tests (Buisson and Ladier, 2009), (Gayah and Daganzo, 2011), (Saberi and Mahmassani, 2012), (Geroliminis and Boyacı, 2012), (Mahmassani et al., 2013).

Recently, the MFD model was further extended to a multi-modal network setting to account for the disproportionate impact of larger vehicles, such as buses, on traffic congestion. For instance, (Geroliminis et al., 2014) proposed a 3D-MFD to investigate the performance of urban bi-modal networks with buses and cars sharing the same road and identified how the performance is influenced by the interactions between modes and the effects of bus stops. (Zheng et al., 2017) proposed an optimization approach for allocating the road spaces for bus lanes in cities, where the optimal spaces shared between different modes were determined to induce a smaller travel cost. (Loder et al., 2017) presented an empirical estimate of a 3D-MFD at the urban scale to characterize the impacts of different travel modes on traffic performance and on each other. (Dantsuji et al., 2021) presented a simulation-based joint optimization framework that integrates dedicated bus lanes and vehicular congestion pricing to minimize the congestion cost based on multi-modal MFD. Notably, (Loder et al., 2022) utilized the MFD as a strategic tool to enhance the performance of a multimodal transportation system, and the advantage of the MFD-based method is its formulation as a mathematical program with equilibrium constraints, enabling a rapid closed-form solution instead of relying on simulation-based methods that often involve unnecessary computational details for strategic decision-making purposes.

2.4 Mitigating Congestion by Parking Provision

The provision of parking spaces is a delicate question and has been extensively studied in the transportation research community (Wang et al., 2019), (Tang et al., 2021). On the one hand, an inadequate supply of parking spaces leads to increased vehicle cruising, which contributes to additional vehicle miles, traffic congestion, and safety hazards. On the other hand, an over-supply of parking spaces leads to insufficient use of land space. The optimal parking provision strategy should carefully balance multiple objectives (Shoup, 2021), including reduced search/cruising distance, increased land space utilization, enhanced traffic flow, and improved road safety.

There are a few works that focus on the optimal provision of on-street parking spaces. For instance, (Millard-Ball et al., 2023) and (Xu et al., 2017) investigated the provision of on-street parking spots for ride-hailing vehicles during idle time between rides to reduce cruising congestion. (Du et al., 2019) developed a mathematical program with equilibrium constraints to determine the optimal placement of on-street parking facilities in the working area where drivers travel through or cruise for parking places in the morning commute. (Wong et al., 2014) used a sequential logit approach to model the bi-level decisions for vacant taxi drivers in customer search and discussed the policy implications of introducing more taxi stands and improving their utilization rates. (Arnott and Inci, 2006b) studied the on-street parking for private vehicles from an economic perspective while considering their cruising behaviors when searching for parking. Various research works have followed (Arnott and Inci, 2006b) to develop analytical frameworks to model the impacts of cruising on traffic congestion. Examples include (Martens et al., 2010b), (Geroliminis, 2015b), and (Cao and Menendez, 2015b) among others.

Some other studies focus on the combination of on-street and off-street parking provisions to improve traffic conditions. For instance, (Qian et al., 2012) investigated how parking fees and parking supplies can be designed to mitigate traffic congestion. They reported that the optimal parking solution could effectively reduce social costs and queuing delays. (Leurent and Boujnah, 2014) provided an analytical model to capture the equilibrium choice of parking and travel routes in a transportation network. Both on-street and off-street parking provisions were considered, and management strategies, including fare, capacity, location, and occupancy rate of parking lots, were examined. (Li et al., 2020) investigated off-street parking for ride-hailing vehicles to reduce cruising traffic and showed that a novel business model that integrates shared parking into the on-demand ride-hailing platform could benefit all stakeholders in the ride-hailing market. (Zhang et al., 2020) considered a parking-space shared problem in urban cities with a hybrid supply of on-street and off-street shared parking spaces. The parking facility choice of users was divided as a network equilibrium, and the

profit-maximum parking provision strategies of the platform were examined.

Distinct from all existing works, our paper investigates the optimal provision of on-street parking spaces for tourist coaches in a bimodal transportation network. The decisions of tourist coach drivers and those of private car travelers follow different patterns, and the impact of coach buses on traffic congestion is also significantly different from that of private vehicles. While no existing works have considered the optimal parking provision for multi-class vehicles in bi-modal transportation networks, our paper fills this research gap.

Chapter 3. Methodology

3.1 Task I: Regulating Curbside Pickup and Drop-off from Tourist Coaches

3.1.1 Problem Statement

This report examines the strategic regulation of curbside pickup and drop-off operations for tourist coaches, aiming to strike a balance between tourist mobility requirements and their impact on local traffic flow. In its capacity as a policymaker, the government implements No-Stop Regulations (NSRs) on specific network links to effectively manage curbside stops for tourist coaches. The implementation of NSRs has profound implications for both road capacity and tourist behavior. On links subject to NSR, tourist coaches are prohibited from stopping in the curbside lane, necessitating tourists to walk to non-NSR links for boarding or alighting. Conversely, non-NSR links permit coach stops for pickup and drop-off activities, albeit at the cost of reduced road capacity. To address this complex trade-off, we have developed a bi-level mixed integer optimization program incorporating equilibrium constraints. At the upper level, the government optimizes NSR placement with the objective of minimizing total network travel time. The lower level models the behavior of private drivers and tourists, who independently minimize their travel costs until an equilibrium state is achieved. For tourist coaches, travel costs are comprehensively defined to include both on-vehicle time and pedestrian walking time. In light of these considerations, we have formulated a link-level network equilibrium model for mixed traffic, encompassing both tourist coaches and private vehicles. Figure 1 provides a visual representation of the system diagram for the proposed analytical framework. This model captures the simultaneous routing decisions of private cars and tourist coaches, which are intricately coupled through the congestion model and the implemented NSRs.

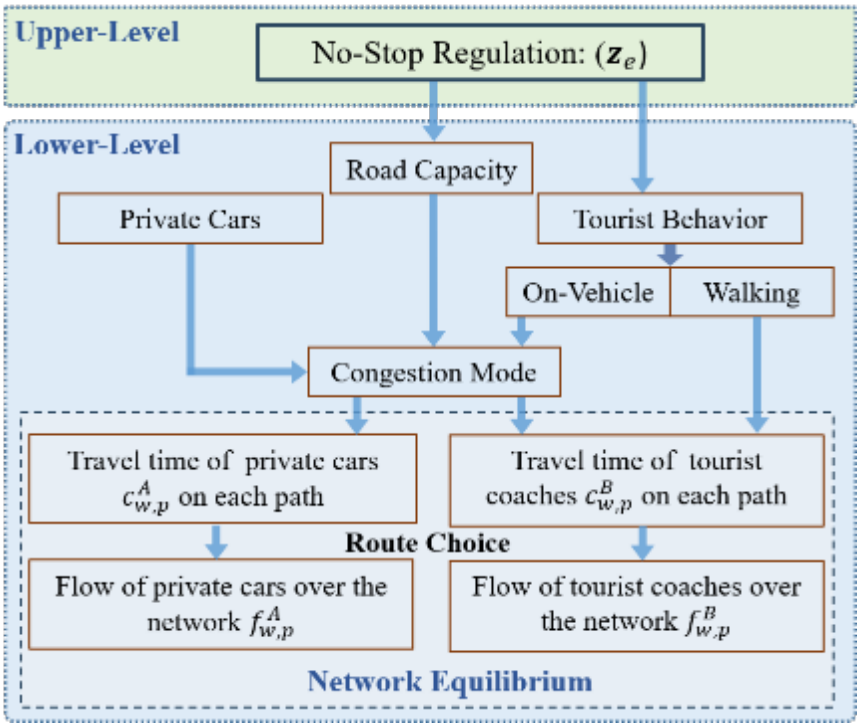

Figure 1 System diagram for the network equilibrium model of mixed traffic

3.1.2 Network Setup

Drawing from the general traffic network depicted in Figure 2, our analysis focuses on a link-level representation of a downtown area. This urban landscape is modeled as a directed graph $G_0(\mathsf{N},\mathsf{E})$, where N denotes the set of nodes and E represents the set of links within the network. Each individual link is designated by $e = 1,...,\mathsf{E}$.

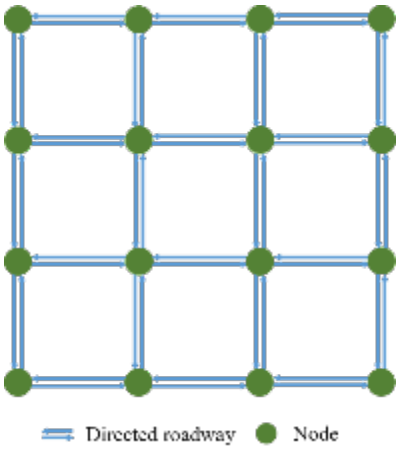

Figure 2 General network

To accurately capture the dynamics of tourist coach pickup and drop-off activities, we adopt the assumption that all travel demands originate and terminate at links. (It is important to

note that link-based demand inherently interacts with node-based network elements. Specifically, demand on links must traverse the connecting nodes, interact with other vehicles in the road network, reach the node connecting to the destination link, and finally arrive at the destination link. Thus, this approach remains consistent with node-to-node demand modeling. For notational convenience, we employ link-to-link demand terminology in subsequent sections. It is worth emphasizing that assuming all travel demands begin at links does not compromise the validity of on-vehicle behaviors or equilibrium conditions, as the flow on links will inevitably traverse the nodes connecting these links.)

In this framework, we categorize demand links as $O \in \mathsf{N}$, representing trip origins, and $D \in \mathsf{N}$, denoting trip destinations. For a specific trip pair, where $r \in \mathsf{O}$ and $s \in \mathsf{D}$ ($r \neq s$), we define a set W_{rs}. to encompass all Origin-Destination (OD) pairs. Each OD pair $w \in W_{rs}$ represents a connection between an origin link $r \in \mathsf{O}$ and a destination link $s \in \mathsf{D}$. The set W is then used to represent the comprehensive collection of all OD pairs, defined as $W = \cup_{(r,s)\in \mathsf{O}\times \mathsf{D}} W_{rs}$.

Our model operates under the assumption that there exists at least one path $p \in P$ connecting each OD pair. These paths are composed of a sequence of road links $e \in \mathsf{E}$. We employ P_w to denote the set of paths connecting a specific OD pair w. Consequently, the complete set of paths across the network is represented as $P = \cup_{w\in W} P_w$.

3.1.3 Modeling Travel Demand

Our analysis considers a network that accommodates two distinct travel modes: private cars and tourist coaches. While these modes share the same road infrastructure, they serve fundamentally different purposes within the urban transportation ecosystem. To accurately reflect the diverse travel purposes within the population, we categorize travelers into two groups based on their mode of transportation:

- Local commuters utilizing private vehicles (Mode A)
- Tourists utilizing tourist coaches (Mode B)

These modes are denoted by $g \in A, B$ respectively. The vehicular demand rate for each Origin-Destination (OD) pair w in transportation mode g is represented as q_w^g. It is crucial to note that our model operates under two key assumptions:

- Travelers who own private cars maintain a fixed mode choice and do not switch to alternative modes of transportation.
- Travelers opting for tourist coaches (Class B travelers) are predominantly organized tourist groups. These individuals typically prepay for transportation services and travel

collectively. Consequently, we assume that the demand for both traveler types remains constant.

Given these assumptions, for any OD pair w, the trip demand for both private cars and tourist coaches should be equal to the aggregate flows on all paths connecting that OD pair. This principle gives rise to the following flow conservation conditions:

$$q_w^g = \sum_{p \in P_w} f_{w,p}^g, \quad \forall g \in \{A, B\}, w \in W, \tag{1.1.1}$$

where:

- q_w^g denotes the trip demand of mode g for a given OD pair $w \in W$
- $f_{w,p}^g$ represents the flow of g-type travelers along path p connecting OD pair w
- P_w is the set of all paths for a given OD pair w

In the subsequent sections, we will conduct an in-depth examination of the regulations governing tourist coach stops and their consequential impact on traffic flow dynamics within the network. This analysis will provide valuable insights for policymakers seeking to optimize urban mobility while balancing the needs of both local commuters and the tourism sector.

3.1.4 The Impact of No-Stop Regulations on Tourist Coach's Behaviors

This section examines the ramifications of No-Stop Regulations (NSRs) on traffic congestion and tourist flow patterns within urban environments. The designation of curbside lanes on specific streets for tourist coach boarding and alighting inevitably reduces road capacity, exacerbating traffic congestion. Conversely, streets subject to NSRs maintain full capacity, facilitating more efficient traffic flow. The specific effects of NSRs on congestion will be addressed in detail in subsequent sections.

Implementation of NSRs necessitates rerouting of tourist coaches to alternative accessible links for passenger boarding or alighting. Consequently, tourists must complete part of their journey on foot to reach their boarding point or final destination. It's important to note that NSRs do not affect local private cars, as these are typically accommodated in garages or parking lots. To formalize our analysis, we introduce a binary variable z_e to represent the regulatory status of a link $e \in \mathsf{E}$ within the traffic system illustrated in Figure 3. Specifically:

- $z_e = 0$ indicates that stopping is prohibited for tourist coaches on link e
- $z_e = 1$ signifies that stopping is permitted on that link

The imposition of an NSR on a specific link alters the flow pattern of tourist coaches, as the actual departure and arrival links for tourists depend on the NSRs in place. Tourists

originating from or destined for a no-stop link must walk to or from an adjacent link for boarding or alighting. Consequently, the path for tourist coach flow comprises two segments: the walking path and the on-vehicle path. This dual-segment approach is depicted in Figure 3, where black dashed lines represent the walking path and blue dashed lines indicate the on-vehicle path for tourist coaches.

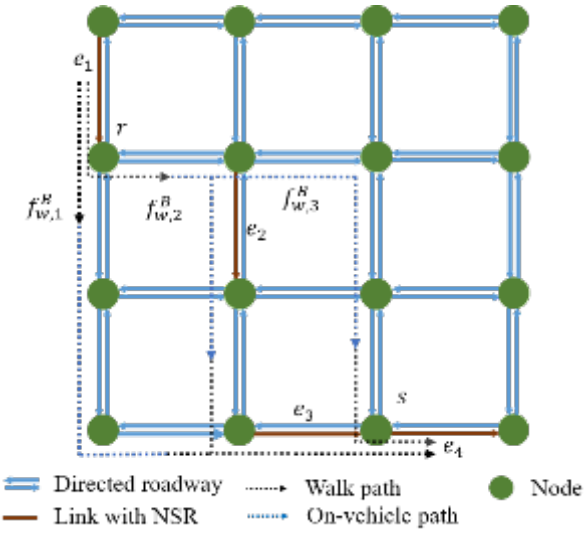

Figure 3 Road network shifting and flows of tourist coaches with no-stop regulations

In analyzing the impact of NSRs on tourist coach paths, we utilize specific indicators to assess the effect on both private car and tourist coach flows. The relationship between these indicators and the paths affected by NSRs are depicted in Figure 4 and Figure 5, derived from Figure 3.

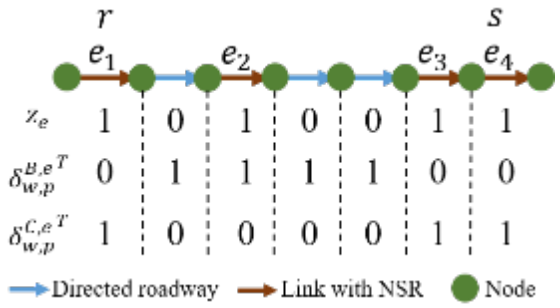

Figure 4 The contribution of path $f^B_{w,2}$ to link flow or walking flow traversed

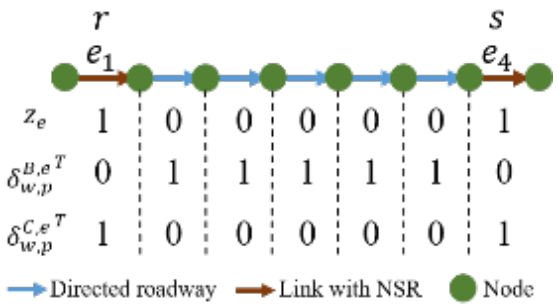

Figure 5 The contribution of path $f_{w,3}^{B}$ to link flow or walking flow traversed

For a specific path p corresponding to an OD pair w, we define the following indicator functions:

- $\delta_{w,p}^{A,e}$ is an indicator variable that takes the value 1 if link $e \in \mathsf{E}$ is part of path p used by private cars connecting the OD pair w and 0 otherwise. This binary indicator helps identify the links utilized by private cars for each specific OD pair and path.
- $\delta_{w,p}^{B,e}$ is an indicator variable set to 1 if link $e \in \mathsf{E}$. constitutes part of the on-vehicle path p for tourist coaches connecting the OD pair w. It signifies that the link is permissible for tourist travel on board. $\delta_{w,p}^{B,eT}$, the transposed indicator of $\delta_{w,p}^{B,e}$, helps illustrate the links within this path that are unaffected by or not imposed on NSRs.
- $\delta_{w,p}^{C,e}$ is an indicator variable set to 1 if link $e \in \mathsf{E}$ is impacted by NSRs on path p for tourist coaches connecting the OD pair w. When $\delta_{w,p}^{C,e} = 1$, it indicates that this link will serve as a walking segment for this path. This indicator considers the influence of NSRs on specific links, where either the head or tail links of path p are affected. $\delta_{w,p}^{C,eT}$, the transposed indicator of $\delta_{w,p}^{C,e}$, provides a representation of the NSR effect on the link e.

The walking segment of each tourist's path varies depending on the location of NSR-imposed links along different routes. This mechanism is illustrated in Figure 3. For instance, given an origin-destination (OD) pair rs and the NSRs imposed on the network, we observe distinct patterns:

- Path $f_{w,1}^{B}$ includes a walking segment at the origin and two walking segments at the destination.
- Path $f_{w,3}^{B}$ features a shorter walking segment only at the end.
- Path $f_{w,2}^{B}$ demonstrates how NSRs can affect different segments of the same route differently, with link e_3 necessitating walking and link e_2 involving on-vehicle travel time.

These examples highlight that the effect of NSRs on tourist coach behaviors is not uniform but depends significantly on their specific location within each path.

Based on our analysis, we define:

- $x_e^A, e \in \mathsf{E}$: Link flow for private cars
- $x_e^B, e \in \mathsf{E}$: Link flow for tourist coaches traveling on the roadway
- $x_e^C, e \in \mathsf{E}$: Flow associated with walking time

The relationship between link flow and path flow for each mode can be mathematically expressed as follows:

$$\begin{cases} x_e^A = \sum_{w \in W} \sum_{p \in P_w} f_{w,p}^A \delta_{w,p}^{A,e}, & \forall e \in \mathsf{E} \\ x_e^B = \sum_{w \in W} \sum_{p \in P_w} f_{w,p}^B \delta_{w,p}^{B,e}, & \forall e \in \mathsf{E} \\ x_e^C = \sum_{w \in W} \sum_{p \in P_w} f_{w,p}^B \delta_{w,p}^{C,e}, & \forall e \in \mathsf{E} \end{cases} \tag{1.1.2}$$

Here, suppose η represents the asymmetric impact of tourist coaches on traffic congestion compared to private cars. The total link flow on a specific link e is given by:

$$x_e = x_e^A + \eta x_e^B, \quad \forall e \in \mathsf{E} \tag{1.1.3}$$

Equations (3.1.2) highlight notable differences between private cars and tourist coaches in terms of their traffic behaviors. Private cars have fixed OD pairs, with travel costs influenced solely by route traffic conditions. Tourist coaches present more complex challenges, occupying more roadway space and potentially obstructing entire lanes during stops.

The implementation of NSRs further complicates tourist coach movement patterns, introducing a walking component to tourist journeys and bifurcating tourist flow into on-vehicle and pedestrian segments. Consequently, $\delta_{w,p}^{B,e}$ and $\delta_{w,p}^{C,e}$ are endogenously determined by the NSR, $z_e, e \in \mathsf{E}$. This comprehensive approach to modeling tourist coach behavior, encompassing both vehicular and walking elements, allows for a more nuanced analysis of traffic patterns in urban areas subject to NSRs. It captures the intricate interplay between regulatory measures, vehicle characteristics, and tourist movement, providing valuable insights for urban planners and policymakers.

3.1.5 The Impact of No-Stop Regulations on Link Travel Time

The implementation of NSRs significantly impacts link capacity and, consequently, the travel

time on each link. To capture this effect, we parameterize the travel time of a link by the NSR status. This relationship is mathematically expressed as follows:

$$t_e = f(\mathbf{f}, z_e), \quad e \in \mathsf{E} \tag{1.1.4}$$

where:

- t_e represents the travel time on link $e \in \mathsf{E}$
- $f(\cdot)$ is a generalized function
- $\mathbf{f}$ is the vectorized form representing the path flows on the network
- z_e is the binary variable indicating the NSR status of link e

This formulation allows us to model the complex interplay between traffic flow, regulatory measures, and travel time. By incorporating the NSR status directly into the travel time function, we can more accurately capture the dynamic effects of these regulations on traffic patterns and congestion levels throughout the network.

The function $f(\cdot)$ encapsulates various factors that influence travel time, including:

- The volume of traffic on the link
- The composition of that traffic (private cars vs. tourist coaches)
- The regulatory status of the link (whether stopping is allowed or prohibited)

This approach offers several advantages:

- Flexibility: The generalized function can accommodate various mathematical models of traffic flow, allowing for adaptability to different urban contexts.
- Precision: By explicitly including the NSR status (z_e), we can capture the nuanced effects of these regulations on travel times.
- Comprehensive analysis: This formulation enables us to analyze how changes in NSR policies might affect travel times across the entire network, not just on individual links.
- Policy evaluation: Policymakers can use this model to predict the outcomes of different NSR configurations, facilitating evidence-based decision-making.

Understanding the relationship between NSRs, traffic flow, and travel time is crucial for effective urban traffic management. This model provides a robust framework for analyzing these relationships, enabling city planners and policymakers to make informed decisions about the implementation and adjustment of NSRs.

3.1.6 Travel Cost for Each Mode

In the sections that follow, we will discuss the incentives for private cars, the incentives and regulations for tourist coaches, and how these interact through the congestion model under NSRs.

Consider a group of passengers traveling from origin r to destination s, denoted by $w=(rs)$, using private cars. The traffic flow $f_{w,p}^{A}$ for this group is determined using a traffic assignment model, which calculates the travel cost, $c_{w,p}^{A}$, for private cars on path p connecting OD pair w. This travel cost is primarily defined by the time spent traveling to the destination and is influenced by several factors including the flow of private cars, the presence of tourist coaches, and the implementation of curbside regulation policies. The travel cost for private cars is defined as follows:

$$c_{w,p}^{A}=\sum_{e\in \mathsf{E}} t_e \delta_{w,p}^{A,e}, \quad \forall w\in \mathsf{W}, \quad \forall p\in \mathsf{P} \tag{1.1.5}$$

here, $c_{w,p}^{A}$ represents the travel cost of private cars on path p connecting OD pair w. t_e is the travel time on link e, which is affected by the combined effect of both private flows and tourist coach flows.

For a tourist group traveling between OD pair w, NSRs significantly impact their journey. Coaches are restricted to government-sanctioned links for passenger pick-up and drop-off. This constraint often necessitates additional walking segments for tourists, either from pick-up points to their on-vehicle origin or from drop-off points to their final destination, incurring extra walking costs. Moreover, once aboard, tourists can only disembark at a feasible point near their destination; intermediate stops for picking up or dropping off passengers are not permitted. This regulatory framework reshapes the travel patterns of tourist groups, influencing both coach routing decisions and the overall tourist experience. The total travel cost for tourist coaches is expressed as:

$$c_{w,p}^{B}=\sum_{e\in \mathsf{E}} \sigma_e \delta_{w,p}^{C,e}+\sum_{e\in \mathsf{E}} t_e \delta_{w,p}^{B,e}, \quad \forall w\in \mathsf{W}, \quad \forall p\in \mathsf{P} \tag{1.1.6}$$

where $c_{w,p}^{B}$ represents the travel cost for tourist coaches on the path p connecting OD pair w. σ_e is the walking time on link e (if $\delta_{w,p}^{C,e}=1$). Therefore, the first term on the right-hand side represents the walking costs on link e for tourists. The second term accounts for the on-vehicle travel time of the tourist coaches.

3.1.7 Bi-modal User Equilibrium

Definition: Under equilibrium, no traveler of a tourist coach can reduce her in-trip time by unilaterally changing the route, and no traveler of a private car can reduce her total trip time

by unilaterally changing her route or travel mode. Given the No-Stop Regulations (NSRs) for the system and assuming the traffic network follows the user equilibrium (UE) principle, the lower-level problem ([LP]) can be formulated as a minimization program:

[LP]

$$\min_{f_{w,p}^{A}, f_{w,p}^{B}} \sum_{e \in \mathsf{E}} \int_{0}^{x_e} t_e(\omega) d\omega + \sum_{e \in \mathsf{E}} \int_{0}^{x_e^C} \sigma_e d\omega \tag{1.1.7}$$

$s.t.$

$$x_e = x_e^A + x_e^B, \quad \forall e \in \mathsf{E} \tag{1.1.8}$$

$$x_e^A = \sum_{w \in W} \sum_{p \in P_w} f_{w,p}^A \delta_{w,p}^{A,e}, \quad \forall e \in \mathsf{E} \tag{1.1.9}$$

$$x_e^B = \eta \sum_{w \in W} \sum_{p \in P_w} f_{w,p}^B \delta_{w,p}^{B,e}, \quad \forall e \in \mathsf{E} \tag{1.1.10}$$

$$x_e^C = \sum_{w \in W} \sum_{p \in P_w} f_{w,p}^B \delta_{w,p}^{C,e}, \quad \forall e \in \mathsf{E} \tag{1.1.11}$$

$$q_w^g = \sum_{p \in P_w} f_{w,p}^g, \quad \forall w \in \mathsf{W}, \quad g \in \{A, B\} \tag{1.1.12}$$

$$f_{w,p}^A \geq 0, \quad \forall w \in \mathsf{W}, \quad \forall p \in \mathsf{P} \tag{1.1.13}$$

$$f_{w,p}^B \geq 0, \quad \forall w \in \mathsf{W}, \quad \forall p \in \mathsf{P} \tag{1.1.14}$$

where the first term is the total on-vehicle travel cost and the second is the total walking cost. This formulation captures the bi-modal nature of the traffic system, accounting for both private cars and tourist coaches, as well as the walking segments required due to NSRs. The objective function minimizes the total travel cost across all modes, subject to flow conservation and non-negativity constraints.

3.1.8 The Optimal Placement of No-stop Regulations

If we consider the minimum total travel time of travelers in the network, the upper-level problem ([UP]) can be formulated as

[UP]

$$\min_{z_e, f_{w,p}^A, f_{w,p}^B} \quad \sum_{e \in \mathsf{E}} x_e t_e(z_e, x_e) + \sum_{e \in \mathsf{E}} x_e^C \sigma_e(z_e) \tag{1.1.15}$$

$$s.t.$$

$$z_e \in \{0,1\} \tag{1.1.16}$$

This optimization is subject to the constraints defined by the lower level problem.

3.1.9 Solution Algorithm

3.1.9.1 SO Relaxation

The bi-level problem's complexity stems from the lack of an explicit relationship between upper-level and lower-level decision variables. However, when users' route choices follow the System Optimal (SO) principle, the problem can be transformed into a single-level optimization problem with two distinct types of decision variables, significantly simplifying the solution process. By employing SO traffic assignment, the bi-level problem with User Equilibrium (UE) constraints can be approximated as a single-level optimization problem. This simplification reduces complexity, making the problem more manageable to solve. Consequently, a road network design decision based on SO traffic assignment can serve as either a good approximate solution for the bi-level problem with UE constraints or a promising starting point for further optimization.

The finite number of feasible upper-level decision variables allows for sorting these decisions in ascending order of total travel time, as defined by Equation (3.1.15), using SO traffic assignment. Each network design decision can then be evaluated by calculating the corresponding total time cost using the UE principle. If the total travel time of a generated solution based on the UE principle is lower than the total travel time of the last solution obtained using the SO principle, it can be considered the global optimum. This is because the total travel time based on the UE principle for any unexplored solution will not be lower than its corresponding SO-based total travel time, which in turn is not lower than the minimum SO-based total travel time among all explored solutions (Wang et al., 2013). This mechanism enables the development of an effective global optimization method for the proposed bi-level problem.

First, shorten the notation of the domain of these variables. According to Equation (3.1.16), let Φ_z be the set of all feasible NSRs defined by

$$\Phi_z := \{\mathbf{z} \mid z_e \in \{0,1\}, \forall e \in \mathsf{E}\} \tag{1.1.17}$$

where $\mathbf{z}$ is the vector of upper-level decision variables defined as $\mathbf{z} := (z_e, e \in \mathsf{E})$.

If $\Phi_z = \varnothing$, it means there are no regulations imposed on the network, which would be an extreme case in the study. Given different NSRs, the traffic flow over the network may perform differently accordingly. Notice that the demand for both modes is fixed, let Φ_f be the set of all path flows. According to Equation (3.1.12), (3.1.13) and (3.1.14), Φ_f defined by

$$\Phi_f := \{\mathbf{f} \mid \sum_{p \in P_w} f_{w,p}^g = q_{rs}^g, f_{w,p}^g \geq 0, w \in W, p \in P_w, g \in \{A,B\}\} \tag{1.1.18}$$

where $\mathbf{f}$ is the path flow vector defined as $\mathbf{f} := (f_{w,p}^g, w \in W, p \in P_w, g \in \{A,B\})$.

We assume that the network is connected and hence $\Phi_f \neq \varnothing$. The set of feasible link flows, according to Equations (3.1.10), (3.1.11) and (3.1.18), is defined by

$$\Phi_x := \{\mathbf{x} \mid x_e = \sum_{w \in W} \sum_{p \in P_w} f_{w,p}^A \delta_{w,p}^{A,e} + \eta \sum_{w \in W} \sum_{p \in P_w} f_{w,p}^B \delta_{w,p}^{B,e}; x_e^C = \sum_{w \in W} \sum_{p \in P_w} f_{w,p}^B \delta_{w,p}^{C,e}, e \in \mathsf{E}, \mathbf{f} \in \Phi_f\} \tag{1.1.19}$$

where $\mathbf{x}$ is the link flow set defined by $\mathbf{x} := ([x_e; x_e^C], e \in \mathsf{E})$. Throughout this study, we assume that the link travel time functions before and after the capacity change are always strictly increasing and convex so that both the UE and SO traffic assignment problems have a unique link flow solution. Therefore, the relaxed problem (RP) when the traffic assignment follows the SO principle, can be formulated as

[RP]

$$\min_{\mathbf{z} \in \Phi_z, \mathbf{f} \in \Phi_f} \sum_{e \in \mathsf{E}} x_e t_e(x_e) + \sum_{e \in \mathsf{E}} x_e^C \sigma_e \tag{1.1.20}$$

Since we will compare the objective function value between UE and SO, we define V_{RP} to represent the objective function value of [RP] and V_{UE} to represent the objective function value of UE under given NSRs $\mathbf{z}^*$ respectively. Given NSRs $\mathbf{z}^* \in \Phi_z$, we have the set of link flow under UE as

$$\Phi_x^{UE}(\mathbf{z}^*) = arg \min_{\mathbf{x} \in \Phi_x} \sum_{e \in \mathsf{E}} \int_0^{x_e} t_e(\omega) d\omega + \sum_{e \in \mathsf{E}} \int_0^{x_e^C} \sigma_e d\omega \tag{1.1.21}$$

where $\Phi_x^{UE}(\mathbf{z}^*)$ is the set of optimal solutions of UE with given NSRs $\mathbf{z}^* \in \Phi_z$. Under the assumption of strictly increasing and convex link travel time functions, $\Phi_x^{UE}(\mathbf{z})$ is a singleton for any $\mathbf{z} \in \Phi_z$. Evidently,

$$\Phi_x^{UE}(\mathbf{z}) \subset \Phi_x, \forall z \in \Phi_z \tag{1.1.22}$$

The distinction between [UP] and [RP] lies in the link flow $\mathbf{x} \in \Phi_x^{UE}(\mathbf{z})$ for [LP] and $\mathbf{x} \in \Phi_x$ for [RP]. In other words, [RP] is a relaxation of [UP], and its optimal objective value serves as a lower bound for [UP]. The optimal solution to [RP] may not necessarily be optimal for [UP]. Solving [RP] allows us to determine the optimal solution $\mathbf{z}$ using SO traffic assignment, and we can calculate the total travel time at UE by fixing the network design decision at $\mathbf{z}$ and solving the corresponding [LP].

To obtain the global solution of [UP], the solutions for the DNDP with SO traffic assignment are explored and sorted sequentially in an order of increasing total travel time, and their corresponding travel times under UE traffic assignment are evaluated. To obtain the second best SO-based network design decision that is not better than $\mathbf{z}$ but is not worse than any other solution, we solve [RP] by excluding the solution $\mathbf{z}$ from the set Φ_z. This can be done by adding the following constraint to [RP]:

$$\sum_{i \in \mathsf{E}} [(1-\overline{z_e})\overline{z_e} + \overline{z_e}(1-z_e)] \leq 2, \quad \forall \overline{\mathbf{z}} \in \overline{\Phi_z} \tag{1.1.23}$$

where $\overline{\Phi_z}$ is the set containing all the generated integer solutions. Constraint (3.1.23) ensures that if $\mathbf{z} = \mathbf{z}^*$, the left-hand side of the constraint is 0, which violates the constraint. On the other hand, if $\mathbf{z} \neq \mathbf{z}^*$, it implies that $\mathbf{z}$ is an unexplored solution. Therefore, constraint (3.1.23) excludes the explored solution $\mathbf{z}^*$ from the set Φ_z while retaining all other solutions.

The bi-level mixed integer problem is relaxed into a single-level mixed integer problem, where the integer variables are NSRs, $\mathbf{z}$, and the continuous variables are path flows, $\mathbf{f}$, on the network. This relaxation simplifies the problem by avoiding the complexity of UE constraints at the lower level. However, it remains a complex problem. We can linearize the [RP] in two steps: linearizing the constraints and linearizing the objective function, to leverage modern techniques, such as *Gurobi* for solving mixed integer linear programs.

3.1.9.3 Outer approximation

This section introduces an Outer Approximation (OA) algorithm designed to solve the proposed bi-level problem with constraints (3.1.23). This approach is tailored to handle the complexities arising from the strategic behavior of tourist coaches in response to NSRs and their subsequent impact on traffic flow and mode choices.

The OA method is particularly effective for Mixed-Integer Nonlinear Programming (MINLP) problems. It operates by iteratively refining a relaxation of the original problem and solving

a series of sub-problems that provide increasingly accurate approximations of the feasible region.

The SO-relaxation serves as a relaxed master problem, providing a lower bound for the original problem when solved. Conversely, solving the User Equilibrium (UE) with given optimal integer solutions (NSRs) serves as a sub-problem, providing an upper bound for the original problem. The procedure for iteratively achieving these lower and upper bounds is as follows: Lower bound: By solving the aforementioned single-level mixed integer problem using the SO relaxation, we obtain a lower bound for the original problem. Upper bound: After solving [RP], we obtain a set of optimal integer variables (NSRs) under a relaxed master problem. By fixing these integer variables in the primal problem, it transforms into a classical UE problem, providing an upper bound for the primal problem. The UE problem with a given integer variable z^* is formulated as follows:

$$\min_{z^*, f^A_{w,p}, f^B_{w,p}} \sum_{e \in \mathsf{E}} \int_0^{x_e} t_e(\omega) d\omega + \sum_{e \in \mathsf{E}} \int_0^{x_e^C} \sigma_e d\omega \tag{1.1.24}$$

s.t.

$$x_e = x_e^A + x_e^B, \quad \forall e \in \mathsf{E} \tag{1.1.25}$$

$$x_e^A = \sum_{w \in W} \sum_{p \in P_w} f_{w,p}^A \delta_{w,p}^{A,e}, \quad \forall e \in \mathsf{E} \tag{1.1.26}$$

$$x_e^B = \eta \sum_{w \in W} \sum_{p \in P_w} f_{w,p}^B \delta_{w,p}^{B,e}, \quad \forall e \in \mathsf{E} \tag{1.1.27}$$

$$x_e^C = \sum_{w \in W} \sum_{p \in P_w} f_{w,p}^B \delta_{w,p}^{C,e}, \quad \forall e \in \mathsf{E} \tag{1.1.28}$$

$$q_w^g = \sum_{p \in P_w} f_{w,p}^g, \quad \forall w \in W, \quad g \in \{A, B\} \tag{1.1.29}$$

$$f_{w,p}^A \geq 0, \quad \forall w \in W, \quad \forall p \in P_w \tag{1.1.30}$$

$$f_{w,p}^B \geq 0, \quad \forall w \in W, \quad \forall p \in P_w \tag{1.1.31}$$

This problem can be efficiently solved using column generation, where paths are added successively throughout the iterative computational procedure.

3.2 Task II: Provision of Hourly Parking for Tourist Coaches

3.2.1 Problem Statement

The government determines parking space allocation $\mathbf{N^A}$ for private cars and $\mathbf{N^B}$ for tourist coaches. The objective is to minimize the total travel time of private drivers and tourists across the bi-modal transportation network, while considering drivers' route choices in response to the parking allocation. At lower level, individual drivers minimize their travel time by choosing optimal routes, given the government's parking space allocation decisions. Figure 2 illustrates the structure of the proposed model, showcasing: connections between the two-level decisions, models at each level and interplay between these elements.

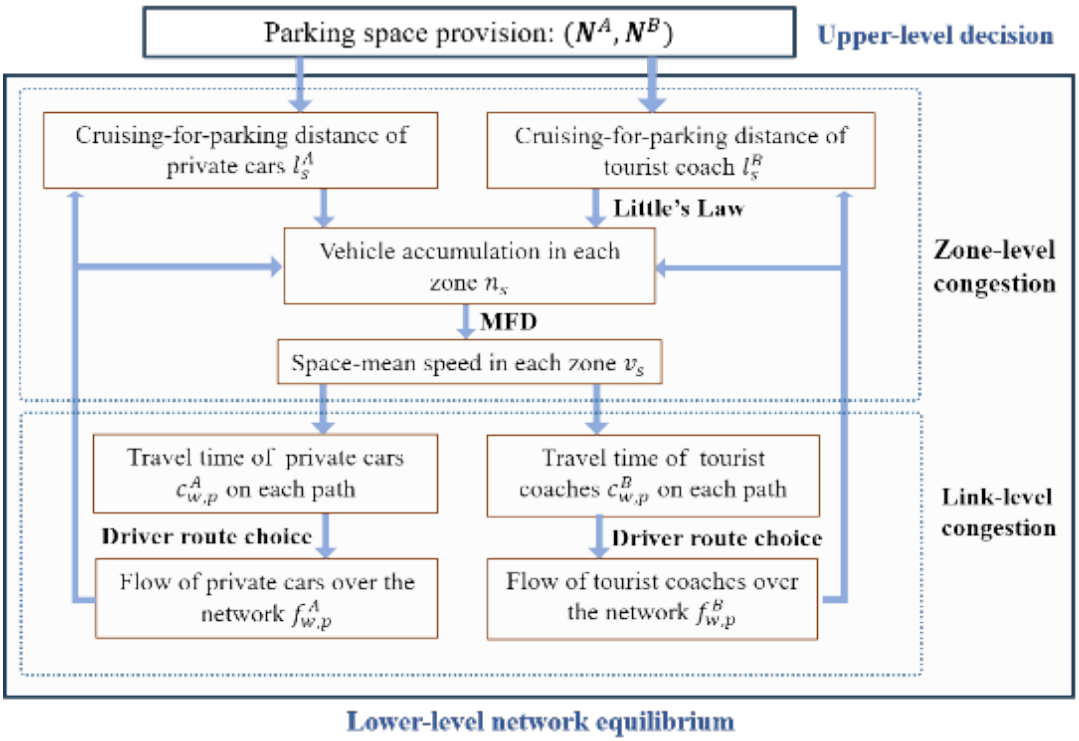

Figure 6 The structure of the proposed bi-level problem

This bi-level approach captures the complex interactions between government planning and individual behavior in the context of urban transportation and parking management. The following sections will elaborate on the technical details of the proposed model, adhering to the structure outlined in Figure 6. Key aspects of this formulation include:

- Integration of parking decisions with traffic flow management
- Consideration of both private cars and tourist coaches in a bi-modal system

- Modeling of individual route choices in response to parking availability

Government optimization of parking allocation to improve overall system performance

This framework allows for a comprehensive analysis of how parking policies can influence traffic patterns and overall transportation efficiency in urban areas with significant tourist activity.

3.2.2 Transportation Networks

We model the urban transportation system using a multi-level network approach. At the granular level, we define a network $G_0(\mathsf{I}, \mathsf{L})$, where I represents major intersections and L denotes road segments connecting these intersections. To capture broader traffic patterns, we partition the city into N zones, each characterized by unique speed-density-flow relationships reflecting distinct road capacities. This zoning divides I into mutually exclusive subsets $\mathsf{I}r$ for each zone r, such that $\mathsf{I} = \cup r \in \mathsf{N} \mathsf{I}_r$.

At the zonal level, we represent the transportation network as a directed graph $\mathsf{G} = (\mathsf{N}, \mathsf{E})$. Here, N denotes the set of zones, and E represents the adjacency between zones. An edge exists in E between zones r and s if they share a boundary. Within each zone r, we identify sets of origin points O_r and destination points D_r, both subsets of I_r, representing trip start and end locations respectively.

To model travel patterns, we define Origin-Destination (OD) pairs. For any two zones r and s, the set W_{rs} encompasses all OD pairs connecting origins in r to destinations in s. The complete set of OD pairs across all zones is denoted by $W = \cup_{(r,s) \in \mathsf{N} \times \mathsf{N}} W_{rs}$. For each OD pair $w \in W$, we assume the existence of at least one connecting path p, composed of a sequence of links $e \in \mathsf{L}$. We use P_w to denote the set of all paths for OD pair w, and $P = \cup_{w \in W} P_w$ to represent the complete set of paths in the network.

This hierarchical network structure allows us to analyze traffic flows and parking allocation at both micro and macro levels, providing a comprehensive framework for addressing urban transportation challenges. It enables the integration of local traffic dynamics with broader zonal patterns, facilitating a more nuanced approach to transportation planning and management.

3.2.3 Travel Demand Model

Our model considers two distinct travel modes: private cars and tourist coaches, each serving different trip purposes. Tourist coach travelers (Class B) are primarily tourist groups who pre-pay for transportation services and are grouped into coaches for their trips. Due to the nature

of these pre-arranged group tours, we assume that the demand rate for tourist coaches, q_w^B, is fixed for each OD pair $w \in W$.

In contrast, potential private car users (Class A) are primarily local residents with greater flexibility in mode choice. As congestion increases, these travelers may opt for alternative modes such as transit. Consequently, we model the demand rate for private cars, q_w^A, as elastic. To characterize the mode choice between private cars and alternatives (e.g., transit, walking, biking), we employ a logit model. Let μ_w^A denote the average cost of private vehicle travel for OD pair $w \in W$, and c_w^0 represent the exogenous cost of alternative options. The demand rate for private cars is then given by:

$$q_w^A = \frac{e^{-(\alpha^A + \upsilon \cdot \mu_w^A)}}{e^{-(\alpha^A + \upsilon \cdot \mu_w^A)} + e^{-(\alpha^T + \upsilon \cdot c_w^0)}} \cdot q_w^{A0}, \quad \forall w \in W \tag{1.2.1}$$

Here, q_w^{A0} is the exogenous arrival rate of potential Class A travelers for OD pair $w \in W$. The parameter υ indicates demand sensitivity to travel time, while α^A and α^T are mode-specific constants. Notably, μ_w^A is endogenously determined by cruising and travel costs, which will be elaborated upon in subsequent sections.

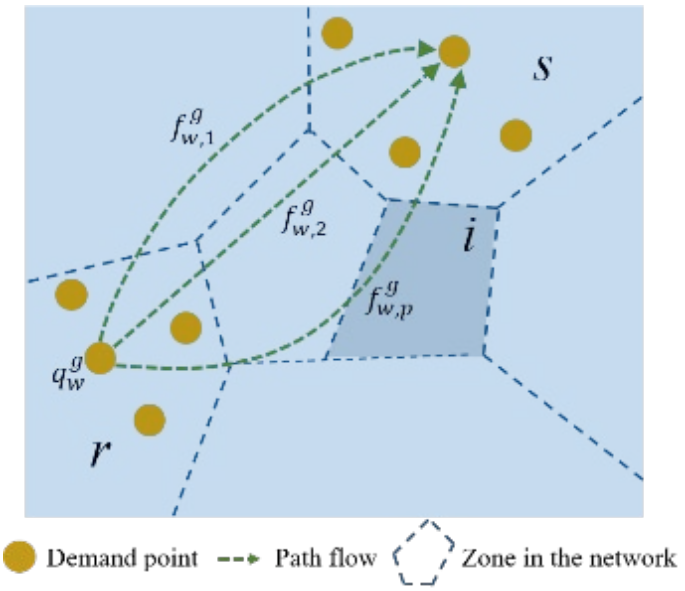

Figure 7 Path flows in the network

For the purposes of this research, we focus on private cars, tourist coaches, and the interactions between them in a city traffic network. Therefore, we assume that the travel mode, g, only includes A, the private car mode, and B, the tourist coach mode. Given OD pair $w \in W$, the trip demand of private cars and tourist coaches should be equal to the flow on all paths connecting the OD pair, which leads to the following flow conservation conditions:

$$q_w^g = \sum_{p \in P_w} f_{w,p}^g, \quad \forall g \in A, B, w \in W \tag{1.2.2}$$

In this equation, q_w^g denotes the trip demand rate of mode g for given OD pair $w \in W$, and $f_{w,p}^g$ represents the flow of g-type travelers along path p that connects OD pair w. P_w is the path set for given OD pair w. This flow conservation principle ensures that the total demand for each mode between an origin and destination is distributed across all available paths connecting that OD pair. It captures the routing choices of travelers within the network while maintaining consistency between overall demand and path-specific flows.

The model allows for a comprehensive analysis of how different types of vehicles (private cars and tourist coaches) utilize the urban road network. By explicitly considering these two modes, we can investigate their distinct impacts on traffic flow, parking demand, and overall network performance. This approach enables us to account for the unique characteristics and requirements of both local commuters and tourist groups in urban transportation planning.

In the following sections, we will delve into the cruising-for-parking behaviors of these two modes and explore their impact on traffic flow in the network. This will include an examination of how parking availability and location affect route choices, travel times, and overall network congestion. By integrating these factors, we aim to develop a more nuanced understanding of urban traffic dynamics and inform more effective transportation and parking policies.

3.2.4 Cruising-for-Parking Behaviors

When travelers arrive at the destination zone, they will look for parking spaces and may have to cruise in the neighborhood if a parking space is not immediately available. The cruising-for-parking behaviors depend on the parking provision strategies of the government and influence the traffic congestion of the transportation network. To characterize these intricate relations, we consider on-street parking where parking spots are not reserved in advance. Drivers would search for parking spots nearby their destination in a zone $s \in \mathsf{N}$ when they finally approach their destination j located in zone s, i.e., $j \in D_s$ (as shown in Figure 8). For each zone $s \in \mathsf{N}$, the total searching flow of g-type vehicle f_s^g is given by:

$$f_s^g = \sum_{w \in \cup_{r \in \mathsf{N}} W_{rs}} \sum_{p \in P_w} f_{w,p}^g, \quad \forall g \in \{A, B\}, s \in \mathsf{N} \tag{1.2.3}$$

where the set $\cup_{r \in \mathsf{N}} W_{rs}$ contains all OD pairs whose trips end at zone s. We assume cruising drivers would drive along the road links to search on-street spaces within each zone $s \in \mathsf{N}$. It is important to emphasize that the behavior of Class A and Class B travelers may

be different: private car drivers typically stay in their vehicle until a parking spot is found, and then walk to the destination, whereas tourists typically disembark the coach after they reach their destination, rather than waiting on the coach until it is parked. Therefore, the cruising-for-parking cost and the walking cost predominantly influence Class A travelers and these elements will be reflected in μ_w^A. This model captures the complex interactions between parking availability, driver behavior, and traffic flow. By distinguishing between private cars and tourist coaches, we can better analyze how different types of vehicles impact urban congestion and parking dynamics. This approach allows for more nuanced policy recommendations, considering the distinct needs and behaviors of local commuters and tourist groups.

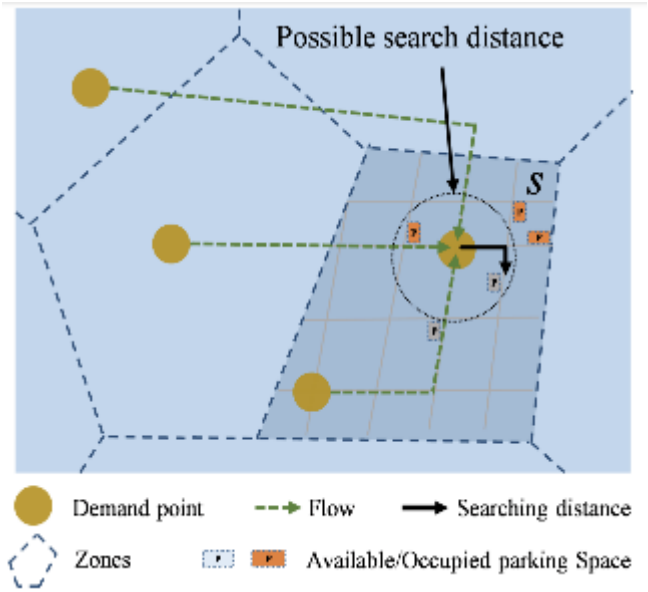

Figure 8 Flow attraction of a demand point and cruising behaviors in a zone

Denote N_s^A and N_s^B as the total number of parking spots assigned to private cars and tourist coaches in zone s, respectively. Let l_s^g be the expected cruising-for-parking distance of g-class travelers g-type vehicles.(Throughout this paper, we will slightly abuse the use of notation g, to refer to both class of travelers and types of vehicles. In particular, $g = A$ refers to local residents or private vehicles, and $g = B$ refers to tourists or tourist coaches.) As more travelers arrive at their destinations, fewer curb parking spaces will be available. Consequently, more vehicles would cruise for parking spots and drivers are expected to experience longer cruising distances l_s^g for $s \in \mathsf{N}$ and $g \in \{A, B\}$. As in (Geroliminis, 2015b), we capture such endogenous relations by modeling cruising-for-parking as Bernoulli trials. More specifically, let $n_s^{g,on}$ be the accumulation of parked vehicles in zone s with class g. Assuming that parking spots are uniformly distributed over all road links in zone s, the probability that a random parking spot is vacant is given by $p_s^g = (N_s^g - n_s^{g,on}) / N_s^g$ for g-type vehicles. Suppose that a driver does Bernoulli trials

with a success probability p_s^g until she finds a vacant spot in zone s. The number of searches before success then follows a geometry distribution and the expectation for g-type vehicle is $1/p_s^g$. Let d_s represent the total length of road links in zone s and d_s / N_s^g be the average distance between two adjacent parking spots for g-type vehicles in zone s. Multiplying d_s / N_s^g by the expected number of searches $1/p_s^g$ yields an expected cruising distance of $d_s / (N_s^g \cdot p_s^g)$ for g-type vehicles in zone s, or equivalently:

$$l_s^g = \frac{d_s}{N_s^g - n_s^{g,on}}, \quad \forall g \in \{A, B\}, s \in \mathsf{N} \tag{1.2.4}$$

Based on Equation (3.2.4) it is clear that the expected vehicle cruising distance decreases with the supply of available parking spots N_s^g and increases with the number of parking vehicles $n_s^{g,on}$. Here, $n_s^{g,on}$ endogenously relies on the total searching flow in zone s and can be expressed as follows:

$$n_s^{g,on} = f_s^g \cdot \tau_s^g, \quad \forall g \in \{A, B\}, s \in \mathsf{N} \tag{1.2.5}$$

where τ_s^g is the average parking duration of each parked g-type vehicle in zone s, which is assumed to be exogenous. For given parking space allocation $\{N_s^g\}$, Equations (3.2.4) and (3.2.5) essentially define the cruising distance l_s^g as a function of network flow vector $\mathbf{f^g} = \{f_{w,p}^g\}_{w \in W, p \in P_w}$ for each type of vehicles g:

$$l_s^g(\mathbf{f^g} \mid N_s^g) = \frac{d_s}{N_s^g - f_s^g \cdot \tau_s^g}, \quad \forall g \in \{A, B\}, s \in \mathsf{N} \tag{1.2.6}$$

where we denote l_s^g as $l_s^g(\mathbf{f^g} \mid N_s^g)$ to emphasize that l_s^g depends on $\mathbf{f^g}$, and is parameterized by the number of parking spaces N_s^g in zone s for type g vehicles.

3.2.5 Traffic Congestion Model

Cruising-for-parking traffic can exacerbate congestion, affecting the travel time of all vehicles within a zone. Consequently, travel time on each road link depends not only on the traversing traffic but also on the parking search flow within each zone. We model traffic congestion using an MFD to account for the impacts of cruising-for-parking behaviors on vehicle travel time.

Assuming that an area is uniformly congested, MFD links the space-mean speed and network flow with the accumulation of vehicles. More specifically, let n be the number of accumulated vehicles in an area, P be the total production (total vehicle kilometers traveled) and v be the space-mean speed. MFD reveals that a stable relation exists between

production P and vehicle accumulation n and space-mean speed can be calculated as $v(n) = P(n)/n$. Regarding the network in our study, each zone $s \in \mathsf{N}$ exhibits distinguished characteristics in terms of road capacity and flow relations. Consequently, the network is unlikely to be uniformly congested in the entire city. To accommodate such heterogeneity, we assume that there exists an MDF for each zone $s \in \mathsf{N}$. Let n_s denote the total number of accumulated vehicles in zone s , which includes both traversing traffic and cruising-for-parking traffic (excluding vehicles that are already parked), then the average traffic speed in zone s , denoted as v_s , is a function of n_s , i.e. $v_s = P_s(n_s)/n_s$, where $P_s(n_s)$ is the production in zone s . Typically, the production in each zone $P_s(n_s)$. is assumed to be a polynomial function of n_s as well as $v_s(n_s)$ (Geroliminis, 2015b).

In the bi-modal transport network, the accumulation of private cars and tourist coaches will both contribute to traffic congestion, thus n_s comprises accumulations from private vehicles and tourist coaches. However, the contributions of private vehicles and tourist coaches are asymmetric: since tourist coach occupies more space, it has a more significant impact on traffic congestion. To capture this, we further decompose the total accumulation n_s as the weighted sum of private vehicle accumulation n_s^A and tourist coach accumulation n_s^B :

$$n_s = n_s^A + \theta \cdot n_s^B, \quad \forall s \in \mathsf{S} \tag{1.2.7}$$

where θ is the parameter to account for the asymmetric impacts that private cars and tourist coaches impose on traffic congestion, which is greater than 1, i.e., $\theta > 1$ representing that tourist coaches occupy more road spaces than private cars. In each zone, s , the vehicle accumulation n_s^A and n_s^B is the sum of the number of vehicles that are searching for on-street parking and the number of vehicles that are traversing zone s (or travel in zone s before reaching a destination in zone s). This can be expressed as:

$$n_s^g = n_s^{g,u} + n_s^{g,0}, \quad \forall g \in \{A, B\}, s \in \mathsf{N} \tag{1.2.8}$$

where $n_s^{g,u}$ stands for the number of g -type vehicles that are searching for on-street parking spaces in zone s , and $n_s^{g,0}$ denotes the number of g -type vehicles that move through zone s with destinations outside s (or with destinations inside s but have not begun to search for a parking space yet). Given the space-means speed as $v_s(n_s)$ in zone s , the vehicle accumulation $n_s^{g,u}$ depends on the expected vehicle cruising distance l_s^g and the total searching flow f_s^g , which can be expressed as follows by applying the Little's law:

$$n_s^{g,u} = f_s^g \cdot \frac{l_s^g}{v_s(n_s)}, \quad \forall g \in \{A, B\}, s \in \mathsf{N} \tag{1.2.9}$$

Similarly, given the network flow $\mathbf{f}^g$ for each vehicle type g, we can calculate $n_s^{g,0}$ as follows:

$$n_s^{g,0} = \sum_{w \in \mathsf{W}} \sum_{p \in P_w} \sum_{e \in \mathsf{L}_s} f_{w,p}^g \delta_e^p \cdot \frac{l_e}{v_s}, \quad \forall g \in \{A, B\}, s \in \mathsf{N} \tag{1.2.10}$$

where L_s is the set of road links that lie within zone s, $\mathsf{L}_s \subset \mathsf{L}$; δ_e^p is a binary parameter such that $\delta_e^p = 1$ if a link $e \in \mathsf{L}$ is a part of path p, and 0 otherwise; l_e is the length of road link e. The term $\sum_{w \in \mathsf{W}} \sum_{p \in P_w} f_{w,p}^g \delta_e^p$ denotes the total amount of flow traversing link e in zone s. The relationship between zone-level vehicle accumulation and link-level vehicle travel time is established by the following proposition:

Proposition 1: The space-mean speed v_s of each zone $s \in \mathsf{N}$ depends on vehicle accumulation and is a function of network flow $\mathbf{f}$ and cruising distance l_s^A and l_s^B:

$$v_s(n_s) \cdot n_s - f_s^A l_s^A - \theta \cdot f_s^B l_s^B - \sum_{w \in \mathsf{W}} \sum_{p \in P_w} \sum_{e \in \mathsf{L}_s} \left(f_{w,p}^A + \theta \cdot f_{w,p}^B \right) \cdot \delta_e^p \cdot l_e = 0, \quad \forall s \in \mathsf{N} \tag{1.2.11}$$

For each one $s \in \mathsf{N}$, the vehicle travel time t_e over each link $e \in \mathsf{L}_s$ is the corresponding link length l_e divided by space-mean speed v_s:

$$t_e = \frac{l_e}{v_s}, \quad \forall e \in \mathsf{L}_s, s \in \mathsf{N} \tag{1.2.12}$$

In Proposition **1**, Equation (3.2.11) is derived from Equation (3.2.7) (3.2.10) by reorganizing/combining the terms related to v_s. Recall that the cruising distance l_s^g relies on network flow $\mathbf{f} = \{\mathbf{f^A}, \mathbf{f^B}\}$ and total parking spaces N_s^g, $\forall g \in \{A, B\}$, we denote the resultant solution of v_s as $v_s(\mathbf{f} \mid N_s^A, N_s^B)$ and the link travel time t_e as $t_e(\mathbf{f} \mid N_s^A, N_s^B)$. This emphasizes that t_e is a function of $\mathbf{f}$ parameterized by the number of parking spaces N_s^A and N_s^B.

3.2.6 Network Equilibrium

For Class A and Class B travelers with the same OD pair $w \in W$, their travel costs may be different because of their distinct travel behaviors: when traveling from origin to destination, a driver of a private car is supposed to choose the path with the least trip time, which includes the travel time on her journey and time for searching for a vacant parking space. In contrast, drivers of tourist coaches are typically required to deliver passengers as soon as possible, and tourists would disembark once they arrive at their destinations. Therefore, we omit the parking search time for Class B travelers when modeling their routing choices, and assume that they would choose the path to minimize the total in-trip travel time. Therefore, for a

given OD pair $w \in W$, the travel time $c_{w,p}^{g}$ associated with each path $p \in P_w$ can be calculated as follows for each vehicle type $g \in \{A, B\}$:

$$c_{w,p}^{g}(\mathbf{f} \mid N^A, N^B) = \sum_{e \in \mathsf{L}} t_e \cdot \delta_p^e + \sum_{s \in \mathsf{N}} \frac{l_s^A}{v_s} \cdot \mathbf{1}(g = A, w \in \cup_{r \in \mathsf{N}} \mathsf{W}_{rs}), \quad \forall g \in \{A, B\}, p \in P_w, w \in \mathsf{W} \tag{1.2.13}$$

where $\mathbf{1}(x)$ is an indicator function, whose value is 1 if its input x is true and 0 otherwise. In (3.2.13), the first term on the right-hand side denotes the total in-trip travel time, and the second term represents a private car's parking search time near its destination. Given the cost, each class of travelers chooses a route with the smallest cost $c_{w,p}^{g}(\mathbf{f} \mid N^A, N^B)$.

Following the user equilibrium principle, we formally define the network equilibrium as follows and refer to it as bi-modal user equilibrium (BIUE) thereafter:

Definition: Under equilibrium, no driver of a tourist coach can reduce her in-trip time by unilaterally changing the route, and no driver of a private car can reduce her total trip time by unilaterally changing her route or travel mode.

Mathematically, given parking space allocation $\mathbf{N^A}$ and $\mathbf{N^B}$, the above network equilibrium stands if there exists aggregate flow $\mathbf{f}^*$, travel demand $\mathbf{q}^{A*} = \{q_w^{A*}\}_{w \in \mathsf{W}}$, and minimum travel time $\boldsymbol{\mu} = \{\mu_w^g\}_{w \in \mathsf{W}, g \in \{A,B\}}$ such that the following conditions are satisfied:

$$\begin{cases} f_{w,p}^{g*} \cdot (c_{w,p}^{g}(\mathbf{f}^*) - \mu_w^g) = 0, \quad c_{w,p}^{g}(\mathbf{f}^*) - \mu_w^g \geq 0, \quad f_{w,p}^{g*} \geq 0, \quad \forall g \in \{A, B\}, w \in \mathsf{W}, p \in P_w \\ \mu_w^A - \mathsf{D}^{-1}(q_w^{A*}) = 0, \quad w \in \mathsf{W} \\ q_w^B - \sum_{p \in P_w} f_{w,p}^{B*} = 0, \quad q_w^{A*} - \sum_{p \in P_w} f_{w,p}^{A*} = 0, \quad \forall w \in \mathsf{W} \end{cases} \tag{1.2.14}$$

where μ_w^g represents the minimum travel time of g-type vehicles between OD pair w, $\mathsf{D}^{-1}(q_w^A)$ stands for the inverse demand function for each OD pair w, which can be derived from (3.2.1). Among these conditions, (3.2.14) states that the travel times on all used paths are less than or equal to the travel times on any unused paths at equilibrium between each OD pair. (3.2.14) suggests that no driver can reduce her travel time by changing her path at equilibrium, and ensures that the trip rate of private cars satisfies demand function (3.2.14) for each OD pair $w \in \mathsf{W}$.

It is difficult to directly work with the BIUE conditions (3.2.14) due to the complex interactions between the endogenous variables encoded in the traffic congestion model as well as the cruising-for-parking behaviors. Fortunately, we find that (3.2.14) can be reformulated as variational inequalities (VI). The following proposition shows how to rewrite

the equilibrium conditions (3.2.14) into an equivalent VI:

Proposition 2: The traffic flow $\mathbf{f}^*$ satisfies the equilibrium condition (3.2.14) if and only if it solves the following VI problem:

$$\sum_{w\in \mathsf{W}}\sum_{p\in P_w}\hat{c}^A_{w,p}(\mathbf{f}^*)\cdot(f^A_{w,p}-f^{A*}_{w,p})+\sum_{w\in \mathsf{W}}\sum_{p\in P_w}\hat{c}^B_{w,p}(\mathbf{f}^*)\cdot(f^B_{w,p}-f^{B*}_{w,p})\geq 0,\quad \forall \mathbf{f}\in\Theta \tag{1.2.15}$$

where the feasible set Θ is defined as $\Theta=\{\mathbf{f}\mid \mathbf{f}\geq 0,\sum_{p\in P_w} f^B_{w,p}=q^B_w,\sum_{p\in P_w} f^A_{w,p}\leq q^{A0}_w,\forall w\in \mathsf{W}\}$; $\hat{c}^g_{w,p}(\mathbf{f}^*)$ denotes the generalized travel time of g-type vehicle along each path $p\in P_w$, which is expressed as follows:

$$\hat{c}^g_{w,p}(\mathbf{f}^*)=\begin{cases} c^A_{w,p}(\mathbf{f}^*)+\dfrac{\alpha^A+\ln(\sum_{p\in P_w} f^{A*}_{w,p})}{\upsilon}-\dfrac{\alpha^T+\ln(q^{A0}_w-\sum_{p\in P_w} f^{A*}_{w,p})}{\upsilon}-c^0_w, & \text{if } g=A \\ c^B_{w,p}(\mathbf{f}^*), & \text{if } g=B \end{cases} \tag{1.2.16}$$

Importantly, Proposition **2** establishes the equivalence between the BIUE conditions (3.2.14) and the VI formulation (3.2.15) which enables us to derive the BIUE by solving (3.2.16). For notation convenience, we concatenate $\{\hat{c}^A_{w,p}\}_{w\in \mathsf{W},p\in P_w}$ and $\{\hat{c}^B_{w,p}\}_{w\in \mathsf{W},p\in P_w}$, and denote it as a vector $\hat{\mathbf{c}}(\mathbf{f}^*)$. The above VI formulation can be expressed in a compact form $\hat{\mathbf{c}}(\mathbf{f}^*)^T(\mathbf{f}-\mathbf{f}^*)\geq 0,\ \forall\ \mathbf{f}\in\Theta$.

3.2.7 The Optimal Parking Space Allocation

In this section, we extend our investigation to determine the optimal allocation of parking spaces between private vehicles and tourist coaches. This space allocation issue is particularly relevant in tourist cities with limited land availability, where identifying new parking areas is challenging, but converting existing spaces between tourist coaches and private cars is more feasible. This analysis further enhances our understanding of the system and provides insights into effective decision-making for parking space management.

We consider the government as the decision-maker who determines the spatial distribution of on-street parking spaces for private cars $\mathbf{N^A}=\{N^A_s\}_{s\in \mathsf{N}}$ and that for tourist coaches $\mathbf{N}^B=\{N^B_s\}_{s\in \mathsf{N}}$ under a constraint that the total space available for parking (regardless of vehicle type) is fixed, denoted by $\overline{N}_s$.

Mathematically, the parking space allocation problem dictates the following mathematical program whose decision variables include the spatial distribution of on-street parking spaces $\mathbf{N}^A=\{N^A_s\}_{s\in \mathsf{N}}$ and $\mathbf{N}^B=\{N^B_s\}_{s\in \mathsf{N}}$:

$$\min_{\mathbf{N}^A,\mathbf{N}^B}\quad \mathbf{c}(\mathbf{f}^*,\mathbf{N}^A,\mathbf{N}^B)^{\cdot}\ \mathbf{f}^* \tag{1.2.17}$$

s.t.

$$\mathbf{N}^A + \beta\, \mathbf{N}^B = \overline{\mathbf{N}} \tag{1.2.18}$$

$$\hat{\mathbf{c}}(\mathbf{f}^*, \mathbf{N}^A, \mathbf{N}^B)^{\cdot} (\mathbf{f} - \mathbf{f}^*) \geq 0, \quad \forall\, \mathbf{f} \in \Theta \tag{1.2.19}$$

$$\mathbf{N}^g \geq \mathbf{0}, \quad \forall g \in \{A, B\} \tag{1.2.20}$$

Where vector $\overline{\mathbf{N}} = \{\overline{N}_s\}_{s\in\mathsf{S}}$ represents the number of on-street parking spaces over the network, the vector $\mathbf{c}(\mathbf{f}^*, \mathbf{N}^A, \mathbf{N}^B)$ is a vector that concatenates $\{c^A_{w,p}\}_{w\in\mathsf{W}, p\in P_w}$ and $\{c^B_{w,p}\}_{w\in\mathsf{W}, p\in P_w}$, which denotes the travel times for private cars and tourist coaches with $c^g_{w,p}$ being defined by equation (3.2.13). In the above optimization problem, constraint (3.2.18) ensures that the total amount of parking space allocated to private cars and tourist coaches does not exceed the space capacity. Parameter $\beta > 1$ delineates the fact that a tourist coach occupies more parking space than a private car. Constrain (3.2.19) forces the network flow $\mathbf{f}^*$ to satisfy the BIUE conditions. Rigorously speaking, the number of parking spaces in (3.2.17) is an integer decision variable. However, since the number of parking spaces is typically large, we do not lose much accuracy by relaxing $\mathbf{N}^A$ and $\mathbf{N}^B$ to be a continuous decision variable. Therefore, in the rest of this study, we treat N^g_s as the continuous decision to facilitate the discussion.

3.2.8 Solution Algorithm

Directly solving problem (3.2.17) is challenging because (3.2.17) includes the VI formulation (3.2.19) parameterized by $\mathbf{N}^s$ as a constraint. The VI (3.2.19) dictates a nonlinear constraint defined implicitly. Consequently, the feasible set is unlikely to be either convex or continuous. In addition, for a given parking allocation plan, multiple flow pattern $\mathbf{f}^*$ satisfying (3.2.19) could exist, and $\mathbf{f}^*$ could be non-differentiable regarding the changes in parking allocation decisions. Considering these challenges, this subsection introduces a solution algorithm that combines Newton method and sensitivity analysis for equilibrium flow to solve the parking space allocation problem (3.2.17).

3.2.8.1 Solution algorithm for network equilibrium

First, a heuristic algorithm is adopted to solve the VI problem (3.2.15), which iteratively updates network flow based on the method of successive averages (MSA) and all-or-nothing traffic flow assignment (Sheffi, 1985), (Nie and Zhang, 2010). To be specific, given a flow pattern $\mathbf{f}_t$ at iteration t, this heuristic algorithm solves the problem:

$$\min_{\hat{\mathbf{f}}\in\Theta} \hat{\mathbf{c}}(\mathbf{f}_t)^T(\hat{\mathbf{f}}-\mathbf{f}_t) \tag{1.2.21}$$

The above problem can be solved by performing all-or-nothing traffic flow assignment, which leads to a new solution $\hat{\mathbf{f}}^*$ that depends on $\mathbf{f}_t$, denoted as $\hat{\mathbf{f}}^*(\mathbf{f}_t)$. A new flow pattern $\mathbf{f}_{t+1}$ is then obtained based on the following update rule:

$$\mathbf{f}_{t+1} = \mathbf{f}_t + \Delta_t / t \cdot (\hat{\mathbf{f}}^*(\mathbf{f}_t) - \mathbf{f}_t) \tag{1.2.22}$$

where Δ_t is an adjustable step size that varies with iteration index t. Such a process will be repeated until the network flow converges.

Despite the simplicity of the above heuristic algorithm, directly applying it to VI problem (3.2.15) is computationally expensive as it requires enumerating all paths that connect each OD pair. However, we note that only a small portion of paths could carry positive flow at user equilibrium. Therefore, to reduce the computation, we integrate the above heuristic algorithm with a column generation approach that expands the path set in each iteration gradually. The algorithm started with two small path sets $\hat{P}^A \subset P$ and $\hat{P}^B \subset P$ for private cars and tourist coaches, respectively. At each iteration t, the paths with the smallest generalized travel time p_w^{g*} are identified for each OD pair $w \in W$ and vehicle type $g \in \{A, B\}$ based on flow pattern $\mathbf{f}_t$. If p_w^{g*} is not contained in set $\hat{P}^g$, we update the path sets by setting $\hat{P}^g = \hat{P}^g \cup p_w^{g*}$. The algorithm then find the optimal $\mathbf{f}^*(\mathbf{f}_t)$ over the updated path set $\hat{P}^A$ and $\hat{P}^B$ instead of the whole path set P. This process continues until no shorter paths can be found or the size of the path set reaches a limit κ. In particular, we start with a zero-flow network, on which we form the initial path set $\hat{P}^A$ and $\hat{P}^B$. Note that the generalized travel time $\hat{c}_{wp}^A(\mathbf{f})$ is undefined when $\sum f_{wp}^A = 0$, we initialize the flow of private cars $\mathbf{f}_0^A$ by calculating q_w^A through the logit model (3.2.1) and assigning q_w^A to the shortest path connecting OD pair w. With these, the algorithm iteratively expands path sets and loads network flow until convergence.

3.2.8.2 Solution Algorithm for Parking Space Allocation

To arrive at a solution for the parking space allocation problem (3.2.17), we first note that the inequality constraint (3.2.18) will always be active at the optimal solution. Therefore, N_s^B can be uniquely determined when N_s^A is given, i.e., by setting $N_s^B = \frac{1}{\beta}\left(\bar{N}_s - \bar{N}_s^A\right)$ for $\forall s \in \mathsf{N}$. In light of this observation, the parametric VI formulation (3.2.19) essentially defines a set-valued mapping from the parameter space formed by $\mathbf{N}^A$ to the space formed by flow pattern $\mathbf{f}^*$. For given $\mathbf{N}^A$, we denote the set formed by $\mathbf{f}^*$ as $\boldsymbol{\Phi}(\mathbf{N}^A)$. The parking space allocation problem (3.2.17) can be reformulated as follows:

$$\min_{\mathbf{N}^A} \min_{\mathbf{f}^* \in \mathbf{\Phi}(\mathbf{N}^A)} \mathbf{c}(\mathbf{f}^*, \mathbf{N}^A)^{\cdot} \mathbf{f}^* \tag{1.2.23}$$

$$s.t. \quad \mathbf{q}^{\mathbf{A0}} \boldsymbol{\tau}^{\mathbf{A}} \le \mathbf{N}^A \le \overline{\mathbf{N}} - \beta \mathbf{q}^{\mathbf{B}} \boldsymbol{\tau}^{\mathbf{B}} \tag{1.2.24}$$

Where $\mathbf{q}^{\mathbf{A0}} = \{q_s^{A0} = \sum q_{rs}^{A0}\}_{s \in \mathbf{N}}$ and $\mathbf{q}^{\mathbf{B}} = \{q_s^B = \sum q_{rs}^B\}_{s \in \mathbf{N}}$ are attraction vectors in each zone, respectively; $\boldsymbol{\tau}^{\mathbf{A}}$ and $\boldsymbol{\tau}^{\mathbf{B}}$ are vectors with elements τ_s^A and τ_s^B, respectively.

In the reformulation (3.2.23), when $\mathbf{N}^A$ is given, a lower-level solution $\mathbf{f}^*$ that solves the inner problem $\min_{\mathbf{f}^* \in \mathbf{\Phi}(\mathbf{N}^A)} \mathbf{c}(\mathbf{f}^*, \mathbf{N}^A)^{\cdot} \mathbf{f}^*$. Therefore, we can view (3.2.23) as a single-level optimization problem with a decision variable $\mathbf{N}^A$, and apply gradient-based algorithms to compute its optimal solution. This requires to compute the gradient of the objective function with respect to $\mathbf{N}^A$. Before presenting the technical details for approximating the gradient, we first note that the lower-level solution $\mathbf{f}^* \in \mathbf{\Phi}(\mathbf{N}^A)$ might not be differentiable with respect to $\mathbf{N}^A$ because it takes values from a set-valued mapping. However, we note that for given a lower-level solution $\mathbf{f}^* \in \mathbf{\Phi}(\mathbf{N}^A)$, we can obtain other lower-level solutions $\tilde{\mathbf{f}}^*(\mathbf{N}^A) \in \mathbf{\Phi}(\mathbf{N}^A)$ that is differentiable with respect to $\mathbf{N}^A$ (Liu et al., 2023). In particular, for a given flow $\mathbf{f}^*$ solving (3.2.19) and an arbitrary positive vector $\boldsymbol{\beta}$, $\tilde{\mathbf{f}}^*(\mathbf{N}^A)$ can be obtained by finding a non-degenerate solution to the linear program:

$$\begin{aligned} &\min_{\mathbf{f} \ge \mathbf{0}} \boldsymbol{\beta}^{\cdot} \mathbf{f} \\ &s.t. \quad \Lambda \mathbf{f}^B = \mathbf{q}^B, \Lambda \mathbf{f}^A = \mathbf{q}^{A*}, \Delta \mathbf{f}^A = \mathbf{x}^{A*}, \Delta \mathbf{f}^B = \mathbf{x}^{B*} \end{aligned} \tag{1.2.25}$$

where $\mathbf{q}^{A*} = \{q_w^{A*}\}_{w \in W}$ is the vector of flows of Class A travelers between each OD pair at the equilibrium f^*; $\mathbf{q}^B = \{q_w^B\}_{w \in W}$ is the vector of flows of Class B travelers between each OD pair, which is assumed to be exogenous; x^{A*} denotes the vector of link flows of Class A travelers induced by f^*; x^{B*} denotes the vector of link flows of Class B travelers induced by f^*; matrix Δ denotes the incidence relations between $\mathbf{f}^g$ and $\mathbf{q}^g$; matrix $\Lambda = \{\delta_e^p\}$ represents incidence relations between path flow f^g and link flow $\mathbf{x}^{g*}$.

In this project, we propose to use the Newton method to obtain the solution to the parking space allocation problem, which iteratively searches parking allocation decisions $\mathbf{N}^A$ by calculating a decent direction based on the first-order gradient, and determines the step size of the update based on second-order gradient. This can be realized by first solving VI (3.2.19) for a lower level solution $\mathbf{f}^* \in \mathbf{\Phi}(\mathbf{N}^A)$, then obtain a non-degenerate solution $\tilde{\mathbf{f}}^*(\mathbf{N}^A)$ by solving the linear program (3.2.25), and finally performing a sensitivity analysis at $\tilde{\mathbf{f}}^*(\mathbf{N}^A)$ to obtain first-order and second-order gradients. The update rule for the Newton method at each step can be represented in the following formula:

$$\mathbf{N}^A = \mathbf{N}^A - \left(\nabla^2_{\mathbf{N}^A} (\mathbf{c}^{\cdot} \mathbf{f}|_{\mathbf{f} = \tilde{\mathbf{f}}^*(\mathbf{N}^A)})\right)^{-1} \cdot \nabla_{\mathbf{N}^A} \left(\mathbf{c}^{\cdot} \mathbf{f}|_{\mathbf{f} = \tilde{\mathbf{f}}^*(\mathbf{N}^A)}\right) \tag{1.2.26}$$

where $\nabla_{\mathbf{N}^A}\mathbf{f}|_{\mathbf{f}=\tilde{\mathbf{f}}^*(\mathbf{N}^{A(k)})}$ and $\nabla^2_{\mathbf{N}^A}\mathbf{f}|_{\mathbf{f}=\tilde{\mathbf{f}}^*(\mathbf{N}^{A(k)})}$ denote the first and second order gradient of the objective function (3.2.17) with respect to $\mathbf{N}^A$ evaluated at $\tilde{\mathbf{f}}^*(\mathbf{N}^A)$, respectively. The process of obtaining $\nabla_{\mathbf{N}^A}\mathbf{f}|_{\mathbf{f}=\tilde{\mathbf{f}}^*(\mathbf{N}^{A(k)})}$ and $\nabla^2_{\mathbf{N}^A}\mathbf{f}|_{\mathbf{f}=\tilde{\mathbf{f}}^*(\mathbf{N}^{A(k)})}$ can be achieved through sensitivity analysis.

Chapter 4. Results and Discussion

4.1 Results of Task I

4.1.1 Data Preparation

We apply the proposed model in Task I to determine the optimal locations for non-stopping restriction and allowable pickup and drop-off locations in two case studies, one for Tsim Sha Tsui and another for To Kwa Wan. The network data comes from the transport department of Hong Kong (Transport Department HK, 2024). This database includes raw information about traffic flow. The network information and link length are collected from *Google Maps* . We abstract the road structure based on map Figure 9 and Figure 12, and then construct it into a network graph with multiple nodes and links, as shown Figure 11 and Figure 13, respectively. According to these data, combined with the calculation method for road capacity adopted in the paper (Manual, 2000), we have the link information like link capacity, lane number of a link, and free flow travel time. We assume that the length of each link is equal to the free flow travel time by choosing appropriate units (Wang et al., 2013).

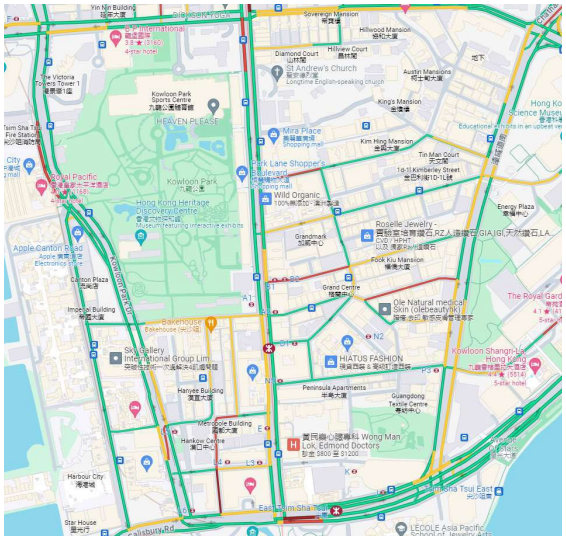

Figure 9 Map of Tsim Sha Tsui

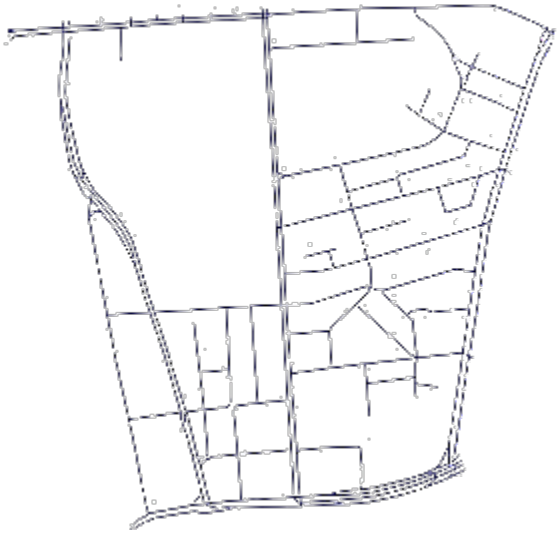

Figure 10 Road structure of Tsim Sha Tsui

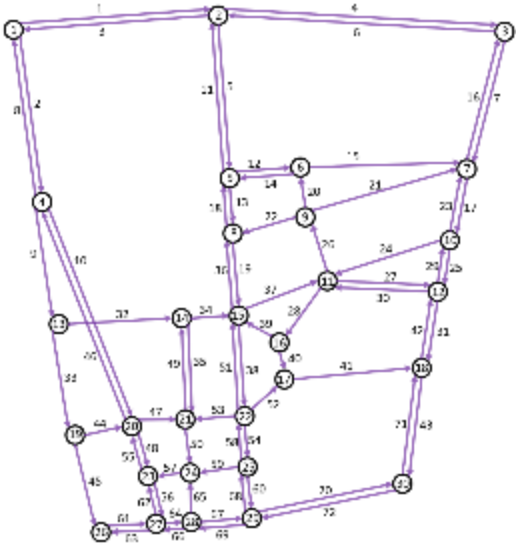

Figure 11 The node-link graph for Tsim Sha Tsui network

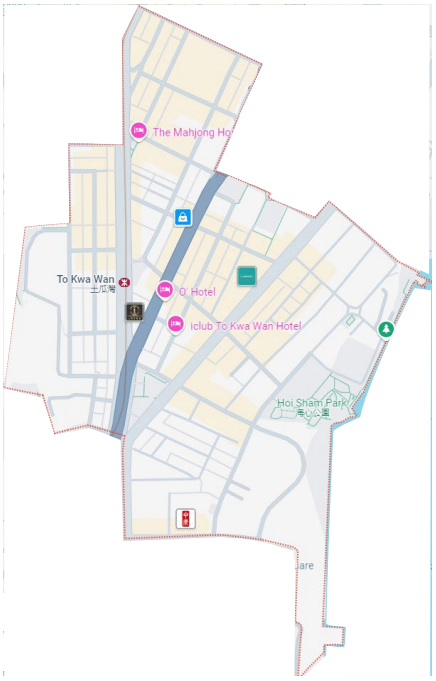

Figure 12 Map of To Kwa Wan

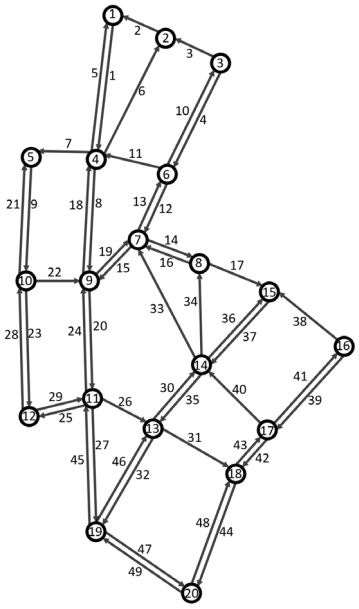

Figure 13 The node-link graph for To Kwa Wan network

Besides, once a link stop is allowed for tourist coaches, a curb-side drive lane will be occupied for tourist coaches to stop. Based on this effect and combined with the Bureau of Public Roads (BPR), the link cost function developed by the U.S., we have the link performance function, which is

$$t_e = t_e^0[1+\alpha(x_e / \sigma_e^{'}(l - z_e))^{\beta}] \tag{1.2.27}$$

where t_e is the travel time to traverse a link $e \in \mathsf{E}$. t_e^0 denotes the free-flow travel time, and $\sigma_e^{'}$ is the capacity of link $e \in \mathsf{E}$, which is affected by the no-stop regulation, z_e. α and β are the model parameters, for which the value $\alpha = 1.5$ and $\beta = 4.0$ are typically used. To account for the walking cost caused by these no-stop regulations, we employ a straightforward linear model, which is

$$\sigma_e = \rho l_e \tag{1.2.28}$$

where σ_e is the walking cost and l_e is the length of link e. ρ is a parameter representing the tourist's walking time.

The OD vectors $\{q_w^A\}_{w \in \mathsf{W}}$ and $\{q_w^B\}_{w \in \mathsf{W}}$ are constructed based on the number of trips produced and attracted at each link provided by (Transport Department HK, 2024). We first derive the trip demand between pairwise zones *rs* by applying the gravity model (Khisty and Lall, 2016a), and then uniformly distribute the zonal trips to the corresponding origin-destination demand point pairs. Specifically, given the number of trips produced and attracted at each district, q_w^g is calculated by the following formula:

$$q_w^g = \frac{1}{|W_{rs}|} \cdot \frac{P_r^g A_s^g F^g(t)_{rs} K_{rs}^g}{\sum_{s=1}^{\mathsf{N}} A_s^g F^g(t)_{rs}}, \quad \forall r \in \mathsf{N}, s \in \mathsf{N} \tag{1.2.29}$$

where P_r^g is the trips produced at zone r for mode g; A_r^g represents trips attracted to zone s for mode g; $F^g(t)_{rs}$ denotes the factor for interchange rs (based on travel time between r and s) for mode g; K_{rs}^g captures the socioeconomic characteristics of zones for mode g. As in (Bouchard and Pyers, 1965a), we set $F^g(t)_{rs} = 1$ and $K_{rs}^g = 1$, respectively.

4.1.2 Performance of the Solution Algorithm

In this part, we analyze the efficiency of the proposed algorithm and the distribution of the NSRs. In real-world road networks, various road types exist, including primary roads, tertiary roads, overpasses, bypasses, and others. Some of these, particularly primary roads and overpasses, are either characterized by high traffic volumes or are unsuitable for curbside stopping due to their design. Consequently, we have disabled certain links whose locations and characteristics make them unsuitable candidates for NSRs. Figure 14 illustrates these disabled links in red arrows. For example, links 10 and 45 are overpasses with limited

shoulder space and high-speed traffic, making them unsafe for tourist coach stops. Links 5 and 11 are primary roads with two lanes each, serving as crucial segments in the network. Their importance for maintaining traffic flow makes them poor candidates for NSRs. Additionally, we've excluded links near emergency services, schools, and other sensitive areas to ensure unimpeded access to these facilities.

After this initial filtering, we applied our acceleration method to identify two extreme cases, including: (a) the smoothest links (Case One): these are links with consistently low congestion levels and relatively steady traffic flow, which are represented by blue arrows in Figure 14; and (b) the most congested links (Case Two): these links experience high traffic volumes and frequent bottlenecks, which are depicted by orange arrows in Figure 14. (we use the case of Tsim Sha Tsui and an illustrative example, while the same method can be applied to To Kwa Wan network.)

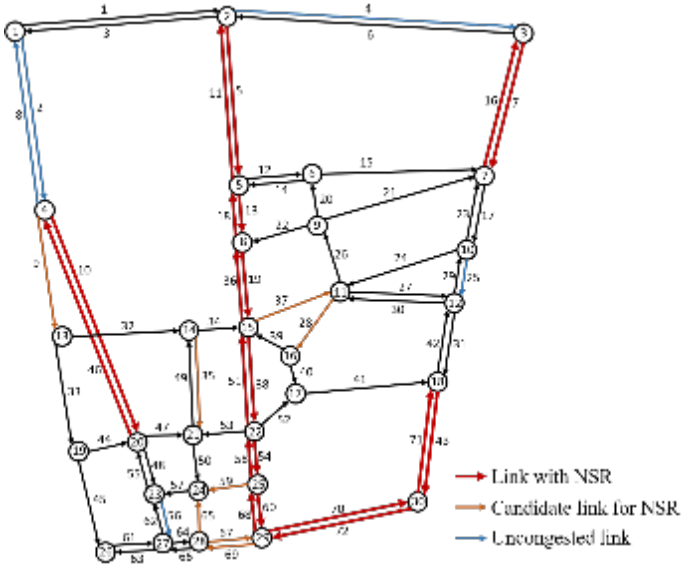

Figure 14 The pretreatment of the network

These two cases can reduce the calculating time in each iteration and are shown in Figure 14 with blue and orange arrows respectively. By focusing on these two cases, we significantly reduced the calculation time in each iteration of our algorithm. This approach allows us to explore the extremes of the solution space efficiently, providing valuable insights into the potential impacts of NSR placement in both low-stress and high-stress network conditions.

In this section, we demonstrate the convergence rate of the proposed method under the Outer Approximation (OA) scheme and compare the performance with and without pre-identification of congested and smooth links. We set the relative optimality tolerance to 0.001. Figure 15 illustrates the progression of the objective function value, lower bound, and upper bound throughout the iterations. Both algorithms implement link thresholds with SO-relaxation, with the key difference being the implementation of pre-identification for smooth

and congested links.

For both methods, the upper bound is obtained in the first iteration and remains constant thereafter. This swift attainment of the upper bound suggests that our method quickly identifies a near-optimal solution, even in complex urban scenarios with high demand for private cars. The initial value of the lower bound objective is identical for both methods, due to the absence of constraints in (3.1.23), even with the pre-identification of smooth and congested links.

As the algorithm progresses, we observe a significant improvement in the lower bound after implementing the pre-identification method for congested and smooth links. This improvement stems from the reduction in the total number of links that need to be enumerated. The blue line represents the objective function value without pre-identification. This approach requires more than 10 times the computational effort compared to the algorithm with pre-identification. The horizontal segments appearing in the latter part of the graph are a result of the threshold method. Because changes in the regulation of certain links have a relatively small impact on overall time consumption, their changes in link cost are relatively small and do not exceed the threshold, resulting in the objective function value remaining essentially unchanged for a certain number of iterations.

In contrast, the convergence rate of the algorithm with pre-identification, shown by the yellow line, is notably faster. This approach significantly improves computing time by identifying links with substantial impact and reducing enumeration time. The result is a dramatic convergence in the lower bound value compared to scenarios without these pre-identifications.

This smoother and more rapid progression indicates that our approach with pre-identification effectively navigates the solution space, avoiding the drastic changes and computational inefficiencies that occur in less constrained formulations. The pre-identification method thus proves to be a valuable enhancement to the algorithm, substantially improving its efficiency in solving complex urban transportation optimization problems.

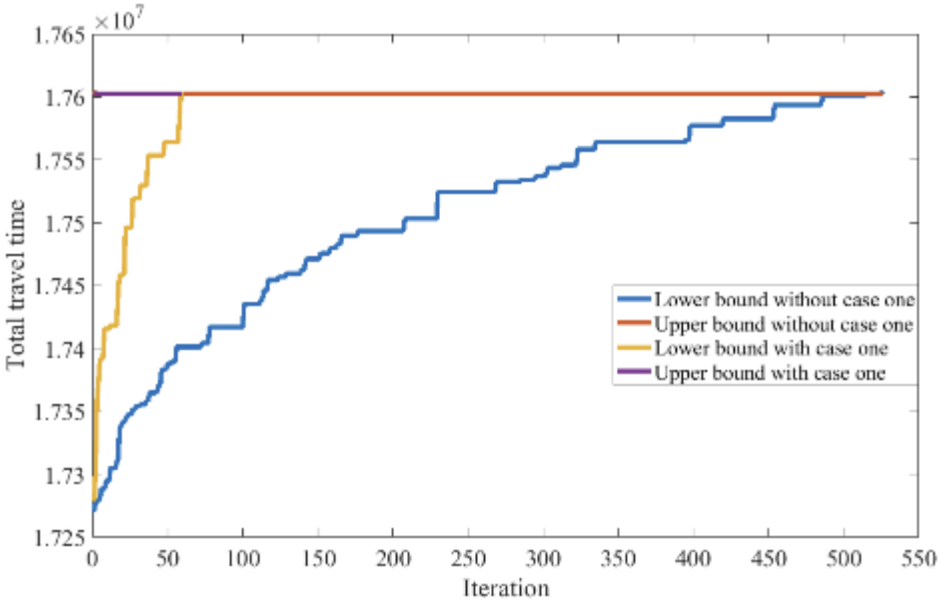

Figure 15 The comparison of algorithm between with and without pretreatment

4.1.3 Results Analysis for Task I

Figure 16 and Figure 17 illustrate the optimal distribution of NSRs in Tsim Sha Tsui and To Kwa Wan, respectively, where NSRs are indicated by red links. Compared with case one (without NSRs in the network), the optimal distribution of NSRs improves 12.1% and 17.3% in total travel time for the two networks.

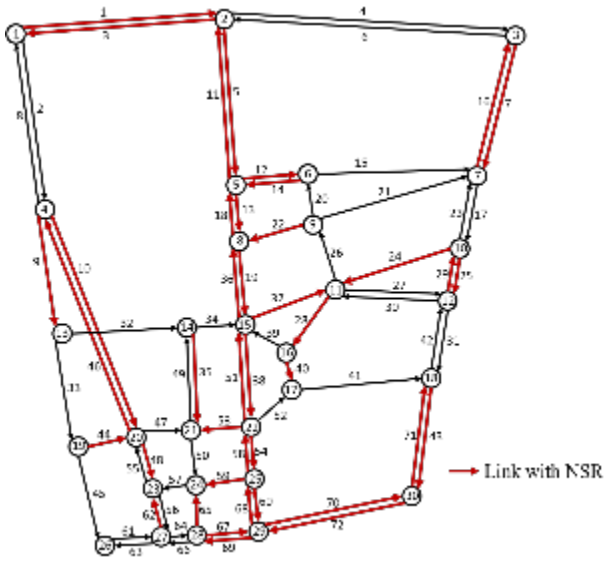

Figure 16 The optimal distribution of NSRs in the Tsim Sha Tsui network

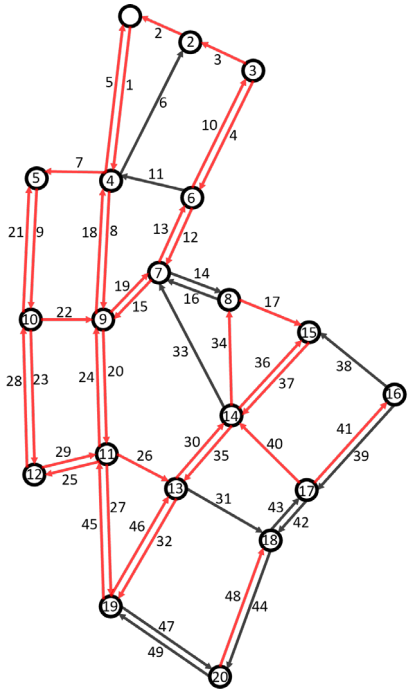

Figure 17 The optimal distribution of NSRs in the To Kwa Wan network

The comparative analysis of simulation results for different regulatory scenarios and Network Service Regulations (NSRs) in Tsim Sha Tsui and To Kwa Wan districts is presented in the following tables.

Table 1 The comparison between different regulations for Tsim Sha Tsui

Tsim Sha Tsui	Action	Travelling cost (en-route cost + walking cost)	Improvement (%)
Case 1	without any regulation	1.76E+07	0
Case 2	rule-based regulation	1.68E+07	4.48
Case 3	optimal regulation	1.48E+07	12.1

Table 2 The comparison between different regulations for To Kwa Wan

To Kwa Wan	Action	Travelling cost (en-route cost + walking cost)	Improvement (%)
Case 1	without any regulation	1.18E+08	0
Case 2	rule-based regulation	1.13E+08	4.2
Case 3	optimal regulation	9.32E+07	17.3

Both tables demonstrate significant improvements in traveling costs under different regulatory schemes, though with varying degrees of effectiveness. In Table 1 and Table 2,

the rule-based regulation represents an intuitive approach where regulations are set based on road congestion levels, requiring some tourists to walk from designated drop-off points to their destinations. This type of regulation is more straightforward to implement as it follows simple rules based on observable congestion patterns.

In Tsim Sha Tsui (Table 1), the implementation of rule-based regulation achieves a notable 4.48% reduction in total travelling costs. When optimal regulation (NSR) is applied, the improvement increases significantly to 12.1%. While this improvement is substantial, it is less significant than in To Kwa Wan due to the more dispersed nature of tourist coaches in Tsim Sha Tsui. The dispersed distribution means that tourist flows are spread more evenly across the network, though the optimization still yields meaningful benefits. To Kwa Wan (Table 2) exhibits even more significant improvements under regulatory interventions. The rule-based regulation achieves a 4.2% reduction in travelling costs, while the optimal regulation results in a remarkable 17.3% improvement. The more pronounced improvement in To Kwa Wan can be attributed to two main factors: a higher concentration of tourist coaches in the area and a more uneven spatial distribution of these coaches. These characteristics provide greater opportunity for optimization through regulatory measures.

The progression from no regulation to rule-based regulation, and then to optimal regulation shows the incremental benefits of more sophisticated regulatory approaches. In both areas, while rule-based regulation provides meaningful improvements, the optimal regulation significantly outperforms it. The additional walking costs introduced by both regulatory schemes are more than offset by the reduction in overall network congestion, resulting in net improvements to total travelling costs.

It's worth noting that while Tsim Sha Tsui's 12.1% improvement might appear modest compared to To Kwa Wan's 17.3%, both represent significant enhancements in network efficiency. The difference in improvement magnitude is not an indication of the regulation's failure in Tsim Sha Tsui, but rather reflects the different underlying characteristics of tourist coach distribution and movement patterns in each area. The data from both areas validates the effectiveness of regulatory interventions, particularly optimal regulation, in reducing total travelling costs. While the more intuitive rule-based regulation provides meaningful benefits, the optimal regulation strategy demonstrates superior performance in both locations, regardless of their different characteristics in tourist coach distribution patterns.

The analysis of the two tables comparing different regulations in Tsim Sha Tsui and To Kwa Wan reveals important insights about traffic management strategies in these areas. In both locations, the restricted segments are primarily implemented along major arterial roads and dense intersections, forming interconnected clusters that suggest a systematic approach to traffic management.

Starting with Tsim Sha Tsui, where the baseline scenario shows a total travelling cost of 1.76E+07, the implementation of rule-based regulation reduces this cost by 4.48% to 1.68E+07. This rule-based regulation, which intuitively assigns restrictions based on road congestion levels and introduces walking costs for tourists, demonstrates moderate effectiveness. When optimal regulation is applied, the improvement becomes more substantial, reaching 12.1% with a reduced cost of 1.48E+07. The pattern of improvement in Tsim Sha Tsui, while significant, is less dramatic due to the more dispersed nature of tourist coaches in this area.

To Kwa Wan exhibits even more pronounced improvements under regulatory interventions. From a baseline travelling cost of 1.18E+08, the rule-based regulation achieves a 4.2% improvement, reducing costs to 1.13E+08. The optimal regulation in this area shows particularly impressive results, with a 17.3% improvement reducing costs to 9.32E+07. This more substantial improvement can be attributed to the higher concentration of tourist coaches in To Kwa Wan and the area's more uneven spatial distribution of tourist activities.

The spatial distribution of restrictions in both areas concentrates on central districts where commercial activities are most intensive. This pattern indicates a careful balance between maintaining traffic efficiency and providing necessary accessibility. The design effectively pushes coach activities toward peripheral or secondary roads while protecting critical junctions and high-flow corridors from potential disruptions caused by coach stopping activities.

The simulation results emphasize the importance of preserving traffic flow on primary corridors while creating natural boundaries for tourist activity zones. This balanced approach effectively reduces potential conflicts between tourist coaches and regular traffic. The data from both areas validates that while rule-based regulation provides meaningful benefits, optimal regulation demonstrates superior performance, particularly in areas with high tourist coach concentrations and uneven spatial distributions. Future refinements should consider seasonal variations in tourist volumes and the evolving needs of the transportation network to ensure continued effectiveness of the traffic management system. Furthermore, to enhance the effectiveness of these regulations, complementary actions can be implemented. These include establishing clear alternative pickup and drop-off points in permissible areas, developing comprehensive signage systems, implementing time-based restrictions during peak hours, and creating dedicated loading bays on secondary roads near tourist attractions. Real-time information systems can also be deployed to assist coach operators in navigation and decision-making.

4.2 Results from Task II

4.2.1 Parameter Calibration and Data Preparation

In this section, we select the Kowloon District, Hong Kong, as the study area to numerically examine the models and solution algorithms proposed in this paper. The study area comprises five sub-districts, namely *Yau Tsim Mong*, *Sham Shui Po*, *Kowloon City*, *Wong Tai Sin*, and *Kwun Tong*, shown in Figure 18. We treat each sub-district as a zone featuring unique MFD representation and traffic characteristics. Within each zone, we generate several demand points for private cars and tourist coaches separately assuming that the trip demand for each vehicle type is uniformly distributed over a zone. The road network that connects all zones and demand points is shown in Figure 4. We use yellow nodes to indicate the origin and destination demand points for private cars, and purple nodes to represent those for tourist coaches. The smaller red nodes do not produce or attract any trips and are recognized as intersections between road links.

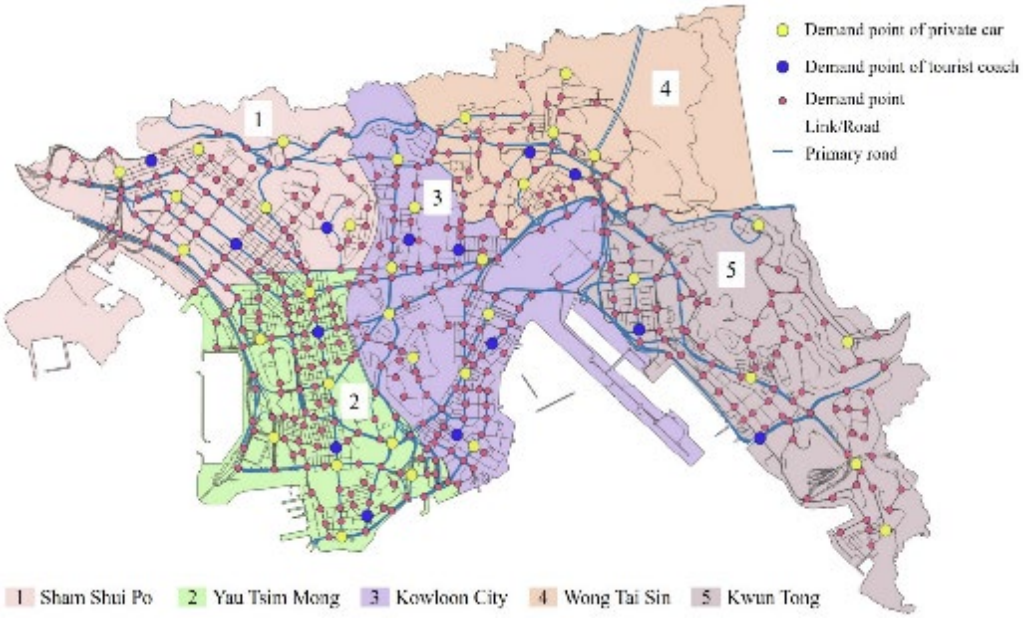

Figure 18 : Study area and road network

The source data of this case study is from the Annual Traffic Census (ATC 2011, Transport Department HK (Transport Department HK, 2011)), and the Travel Characteristic Survey of the year 2011 in Hong Kong (hereafter referred to as TCS 2011). Leveraging the traffic counting stations distributed over Hong Kong, ATC 2011 recorded the bidirectional vehicular flow across various types of roads regarding different vehicle types, the variations in hourly and daily traffic patterns, the location of counting stations, and road occupancy. Through surveys, TCS 2011 collected comprehensive information on travel characteristics, including the population demographics, and the characteristics of trips made by Hong Kong residents and tourists.

According to TCS 2011, the evening peak hour for tourist trips (6:00 p.m.-7:00 p.m.) corresponds to the commuting peak hours for Hong Kong residents. Therefore, our case study considers the evening peak hour on a typical weekday during a tourist season. The number of parking spaces $\{\bar{N}_s\}$ is obtained from the (Legislative Council HK, 2021), which includes both on-street parking spaces and off-street parking spaces. In this part, we assume that the space-mean speed v_s in each zone s is a linear function concerning n_s:

$$v_s = a_s \cdot n_s + b_s, \quad \forall s \in \mathsf{N} \tag{1.3.1}$$

where parameters a_s and b_s are zone-specific and satisfy $a_s < 0$ and $b_s > 0$ $\forall s \in \mathsf{N}$. The values of these parameters can be empirically calibrated either through realistic simulation or real data (Geroliminis, 2015b), (Gayah and Dixit, 2013). We emphasize that the mathematical model and analytical derivation in the rest of this paper do not rely on the specific form of (4.2.1). The assumption of a linear relation is imposed mainly to ease the exposition. Note that when $\mathbf{f}$, l_s^A and l_s^B are given, (3.2.11) defines a quadratic equation for v_s, which may have two distinct solutions. (If the speed v_s is a more complicated function of n_s, we can still derive the relation between v_s and other endogenous variables, and the value of v_s can be derived numerically.) However, in such a case, the solution with a higher value of v_s lies in the uncongested state where the network production increases with vehicle accumulation (Daganzo, 2007). For simplicity, we will keep the solution with a lower value of v_s whenever there exist multiple solutions to (3.2.11), implicitly assuming the city is in the congested regime. (Note that one can also keep the hyper-congested solution and analyze the results based on this solution. It will not affect the methodology proposed in this paper.)

Therefore, the parameters of the MFD a_i and b_i can be calibrated using data from (Transport Department HK, 2024), which includes traffic information collected from 787 detectors during the counting period from 5:00 am to 10:00 pm. The length of each road link l_e together with the historical space-mean speed v_s are obtained from Google Maps and (Transport Department HK, 2024). Based on these inputs, we calculate the production of each zone as $\sum_e x_e l_e$ and the historical vehicle accumulation as $n_s = \sum_e x_e l_e / v_s$. Figure 19 shows the production and the vehicle accumulation for each zone. The parameter b_s is set as the free-flow traveling speed within each zone s, which is calculated based on road length and free-flow travel time. Parameter a_s is calculated as $(v_s - b_s)/n_s$ by equation (4.2.1) with the estimation of v_s, n_s and b_s. The final calibration results for MFD parameters are listed in Table 3.

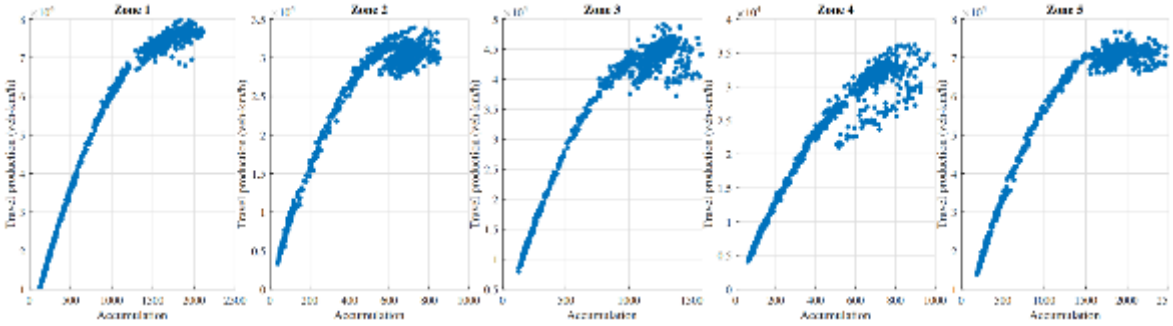

Figure 19 Relationship between accumulation and travel production in each zone

The OD vectors $\{q_w^{A0}\}_{w\in \mathsf{W}}$ and $\{q_w^{B}\}_{w\in \mathsf{W}}$ are constructed based on the number of trips produced and attracted at each district provided by TCS 2011. We first derive the trip demand between pairwise zones rs by applying the gravity model (Khisty and Lall, 2016b), and then uniformly distribute the zonal trips to the corresponding origin-destination demand point pairs. Specifically, given the number of trips produced and attracted at each district, q_w^g is calculated by the following formula:

$$q_w^g = \frac{1}{|W_{rs}|} \cdot \frac{P_r^g A_s^g F^g(t)_{rs} K_{rs}^g}{\sum_{s=1}^{\mathsf{N}} A_s^g F^g(t)_{rs}}, \quad \forall r \in \mathsf{N}, s \in \mathsf{N}. \tag{1.3.2}$$

where P_r^g is the trips produced at zone r for mode g; A_r^g represents trips attracted to zone s for mode g; $F^g(t)_{rs}$ denotes the factor for interchange rs (based on travel time between r and s) for mode g; K_{rs}^g captures the socioeconomic characteristics of zones for mode g. As in (Bouchard and Pyers, 1965b), we set $F^g(t)_{rs} = 1$ and $K_{rs}^g = 1$, respectively.

Regarding model coefficients, we set α_A and α_T in the logit model (3.2.11), as 1\$ (Liu et al., 2023) and the sensitivity parameter υ as 1\$/hr. The average travel time of an alternative mode c_w^0 is supposed to be equal to the free flow travel time for each OD pair $w \in \mathsf{W}$. The average parking duration τ_s^g is set to be 3.5hr for private cars and 3.5hr for tourist coaches in each zone $s \in \mathsf{N}$. We estimate that the length of a tourist bus is about double that of a private car (Planning Department, 2018), thus parameters θ and β, which indicate that a tourist coach occupies more road space than a private car, are set as 2.5. Table 4 summarizes the parameters regarding network setup and model coefficients.

Table 3 Network parameters and model coefficients

Zone	Number of on-street parking spaces $\bar{N}_s$	MFD parameters	
		a_s	b_s

1: Sham Shui Po	39169	-0.0113	58.4
2: Yau Tsim Mong	35245	-0.0339	64.3
3: Kowloon City	52487	-0.0138	49.4
4: Wong Tai Sin	24555	-0.0221	53.7
5: Kwun Tong	55643	-0.0097	52.0

Table 4 Network parameters and model coefficients

Parameters and description	Value	Parameters and description	Value
Number of links	1462	Number of nodes	458
Number of origins for Ar	35	Number of origins for B	14
Number of destinations for A	35	Number of destinations for B	14
Number of OD pair for A	1190	Number of OD pair for B	182
Parking duration for A τ_s^A	3.5hr	Parking duration for B τ_s^B	4.5hr
Logit model parameter α^A	1$	Logit model parameter α^T	1$
Demand sensitivity parameter υ	1$/hr	Parameter for tourist coaches β	2.5
Parameter for tourist coaches θ	3		

Since parking allocation plans impact drivers' cruising for parking behavior, they will inevitably affect exhaust emissions, considering that road transport is a major source of such emissions. In this case study, we use the emission of carbon dioxide (CO_2) to analyze the environmental effects that different parking space allocation plans could impose. We quantify CO2 emissions using the model introduced by (Ntziachristos et al., 2009) and (Ingole et al., 2020) that links the emission rate of exhaust gas to mean vehicle speed. Specifically, this model fitted the recorded unitary emission factors of CO_2 using fourth-degree polynomial functions regarding vehicle speed:

$$EF_{CO_2}(v_s) = \xi_1 v_s^4 + \xi_2 v_s^3 + \xi_3 v_s^2 + \xi_4 v_s + \xi_5, \quad \forall s \in \mathsf{N}, \tag{1.3.3}$$

where $\xi_1, \xi_2, \xi_3, \xi_4, \xi_5$ are the coefficients of the regression model and take values $4.15e^{-6}, -1.04e^{-3}, 0.1, -4.47$ and 123.54, respectively (Ingole et al., 2020). For each zone $s \in \mathsf{N}$, the total emissions of CO2 are calculated as the product of the unitary emission factors and the total distance traveled by all vehicles. The latter is calculated as the total

vehicle kilometers traveled or the production P_s. With this, at equilibrium, we determine the emission of carbon dioxide EM_s for each zone s as

$$EM_s = EF_{CO_2}(v_s) \cdot P_s, \quad \forall s \in \mathsf{N}. \tag{1.3.4}$$

4.2.2 Performance of the Solution Algorithm

We present the convergence performances of proposed in Figure 20 and Figure 21, respectively. For the MSA-based column generation algorithm, we set the step size Δ_t as 0.85 throughout the experiments. Fixed the parking allocation plan $\mathbf{N}^{\mathbf{A}}$ at its optimal solution, Figure 20 shows the variations in the total travel time during the solution process for equilibrium flow $\mathbf{f}^*$. The convergence of the proposed algorithm can be readily observed.

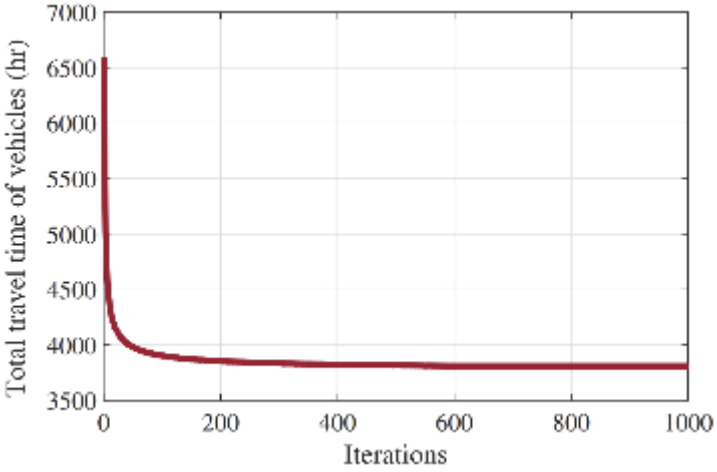

Figure 20 The convergence performance of MSA-based column generation algorithm

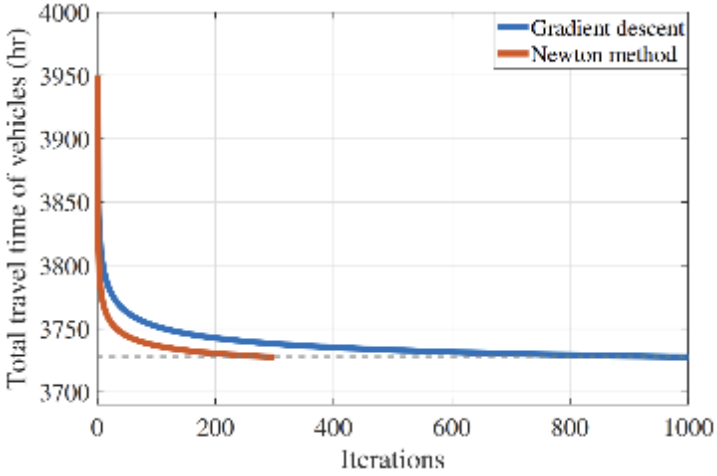

Figure 21 The convergence performance of the Newton and gradient descent methods

To evaluate the proposed Newton method, we introduce a gradient descent method as a

benchmark algorithm that iteratively updates parking space allocation plans $\mathbf{N}^{A(k+1)}$ using the first-order derivative information at $\mathbf{N}^{A(k)}$ in each iteration k, i.e., $\mathbf{N}^{A(k+1)} = \mathbf{N}^{A(k)} - \eta \nabla_{\mathbf{N}^A} \mathbf{c}^{\cdot} \mathbf{f}|_{\mathbf{f}=\tilde{\mathbf{f}}^*(\mathbf{N}^{A(k)})}$, where η is the step size. As shown in Figure 21, the proposed Newton method exhibits a higher convergence rate compared to the gradient descent method. When using the same convergence tolerance, the Newton method converges in 289 iteration steps, whereas the gradient descent method requires 1000 iteration steps. Additionally, the running time for the Newton method is about 15694s, a 65.8% reduction compared to that of the gradient descent method (i.e., 45893s). These results highlight the superior efficiency and faster convergence of the Newton method in comparison to the gradient descent method. The quick convergence of the Newton method can be attributed to its ability to incorporate second-order derivative information. This is particularly effective for the problem under consideration because evaluating the objective function (3.2.17) and solving the VI problem (3.2.19) are time-consuming.

4.2.3 Optimal Parking Provision

Figure 22 illustrates the optimal distribution of parking spaces for each mode across various zones, while Figure 23 depicts the proportion of spaces allocated to private vehicles compared to the proportion of private vehicle traffic in total traffic flow (in terms of traffic attraction) in each zone. An interesting observation is that in all zones, the proportion of parking spaces designated for private vehicles is consistently lower than their share of traffic.

This discrepancy is not only due to the larger size of tourist coaches and their greater impact on traffic congestion but also, more crucially, to the intuition that when travel demand is elastic, the relatively scarce availability of parking for private cars could deter individuals from opting for private car, as the cost of searching for parking at their destination increases. In this scenario, a restricted parking provision strategy not only lowers the overall travel cost but also reduces the cruising for tourist coaches, as well as promotes a shift from private car use to more sustainable alternative modes of transportation, such as transit. This underscores the complex dynamics between private vehicles, tourist coaches, and other transportation modes within a bimodal transportation network.

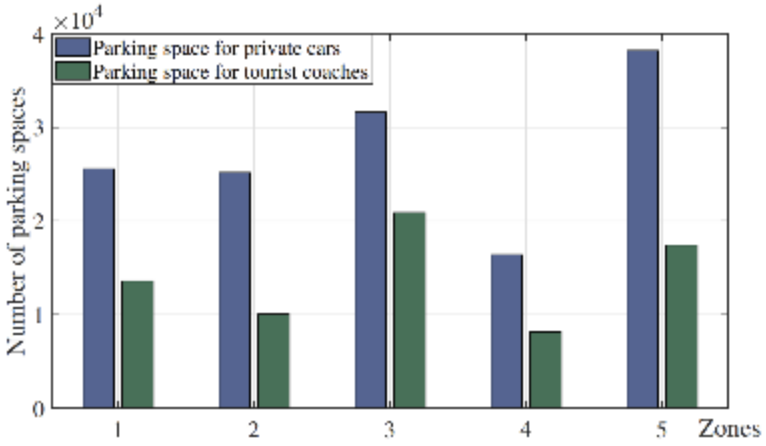

Figure 22 Optimal parking space allocation plan

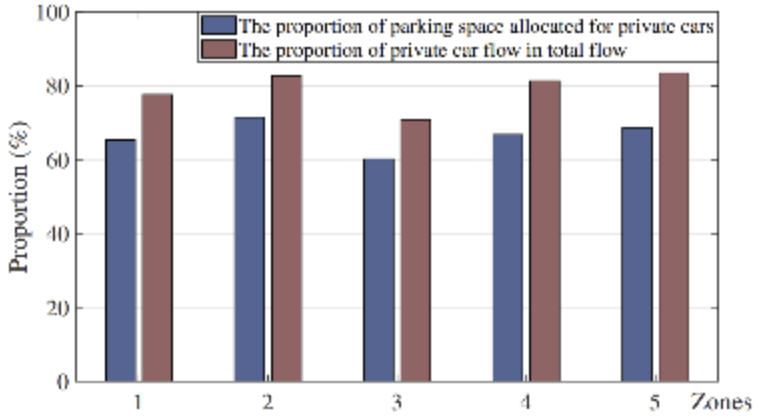

Figure 23 Comparison between the parking space and attraction of private car in ratio

To show the value of optimal parking space provision strategies derived from the proposed framework, we consider the status quo distribution of parking spaces as a benchmark (BM). The number of on-street parking spaces for private cars and private coaches in the benchmark is shown in Figure 24. The data is from (Transport Department HK, 2024). We calculate the network equilibrium in the benchmark by column generation and compare the results against that under the optimized parking allocation plans (OP). The results are summarized in Figure 24 and Figure 25:

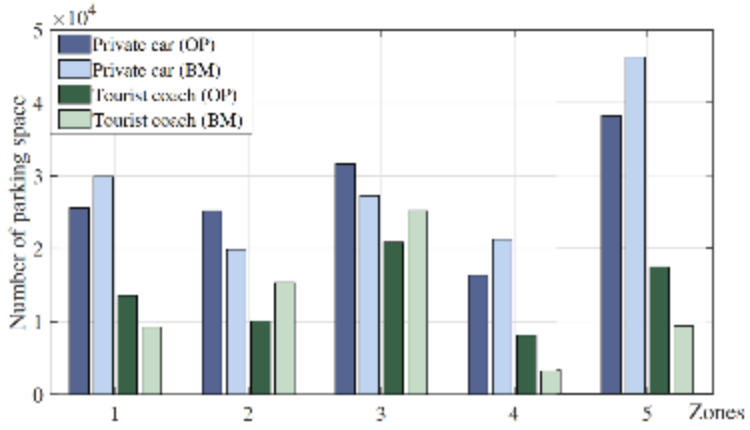

Figure 24 Parking space assignment for each zone

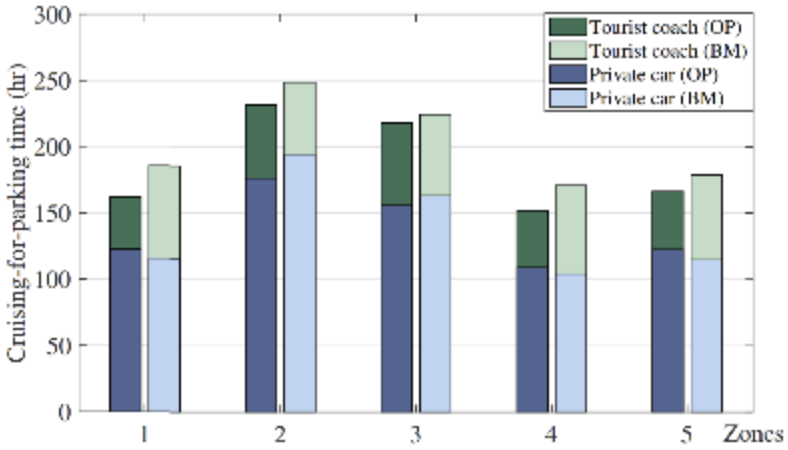

Figure 25 Cruising for parking time in each sub-zone

The terms "OP" and "BM" in Figure 25 represent the optimized parking space plans and the benchmark, respectively. Figure 24 compares the distribution of on-street parking spaces for each vehicle type in each zone under the benchmark and the optimized parking space allocation plans. In Figure 25, the first bar represents the total travel time spent by private cars cruising for parking in Zone 1, and the same explanation applies to the other three bars along the horizontal and vertical axes. In all zones, there is a positive correlation between increased parking space and reduced cruising-for-parking traffic. Specifically, a larger (or smaller) quantity of parking spaces for private vehicles in the OP scenario compared to the BM scenario results in a smaller (or larger) cruising-for-parking time in the OP scenario relative to the BM scenario. Further, the simulation results reveal a significant discrepancy between the current parking space allocation and the optimal allocation strategies in Zone 2, Zone 4, and Zone 5, particularly for tourist coach parking. This underscores the importance of the proposed approach in pinpointing the zones with the most pronounced potential for enhancement.

Figure 25 illustrates the reduction in total cruising-for-parking time achieved by the

optimized plan (OP) compared to the benchmark (BM), resulting in substantial time savings. The decrease in total cruising time for each zone is attributed to the implementation of a rational parking provision, specifically an optimal parking provision. This provision effectively reduces the time spent cruising for parking in each zone, resulting in lower accumulations compared to the benchmark. As a result, the space-mean speed in each zone increases, leading to a considerable reduction in overall cruising time.

Specifically, the optimized plan saves more than 50 hours and 64 hours of cruising time for private cars and tourist coaches, respectively. This reduction corresponds to a decrease of 4.2% and 23.3% for private cars and tourist coaches, respectively, in terms of cruising time. Moreover, the optimized plan leads to a 7.8% decrease in overall cruising time for the entire city.

These results suggest that the allocation of on-street parking spaces between private cars and tourist coaches does affect vehicles' cruising-for-parking time and hence their route choices, which justifies our use of parking space allocation plans to regulate system travel times.

Table 5 Space-mean speed comparison under OP and BM

Zones	Space-mean speed (km/h) (BM)	Space-mean speed (km/h) (OP)	Rate of speed improvement (%)
1	40.47	41.17	1.73
2	41.46	42.27	1.96
3	32.60	33.00	0.89
4	34.36	35.31	2.78
5	43.09	44.02	2.14

Table 5 presents the space-mean speeds for each zone under different strategies, as discussed in the analysis of the parking space assignment comparison. The impact of parking provision on space-mean speeds cannot be ignored, as it demonstrates a noticeable influence on the overall network. These results highlight that a well-planned and reasonable allocation of parking spaces can affect traffic conditions within the studied area.

The findings suggest that a relatively small change in parking provision (i.e., reorganization of parking space types) can lead to noticeable variations in space-mean speeds, indicating the interconnected nature of parking availability and traffic flow. This underscores the importance of considering parking space allocation as an integral part of transportation planning and management.

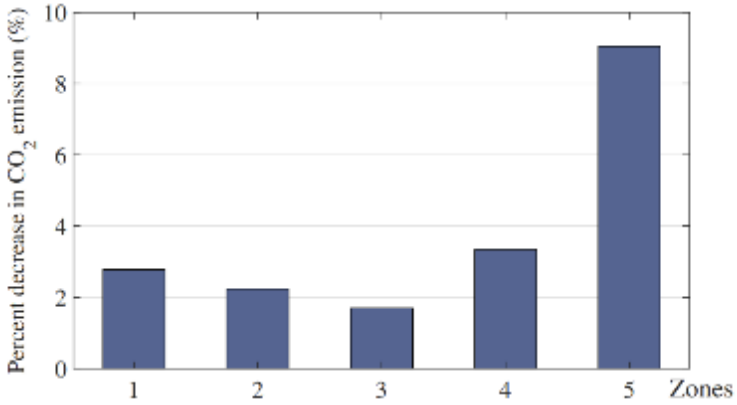

Figure 26 The percent decrease in CO2 emission compared with the benchmark

Figure 26 illustrates the percent decrease in CO_2 emissions across all zones under the optimal parking space allocation plan as compared to the benchmark. Figure 26 indicates that implementing the optimal parking allocation plan would lower CO_2 emissions across all zones, with Zone 5 experiencing a particularly significant reduction. Such environmental benefits stem from reduced vehicle accumulation and private vehicle usage under the optimal parking space allocation plan. On the one hand, the optimal parking space allocation plan results in overall lower vehicle accumulation and consequently higher space-mean speeds in each zone compared to the benchmark case, hence reducing the total CO_2 emissions. On the other hand, fewer parking spaces are available for private cars under the optimal parking space allocation plan than under the benchmark policy. Therefore, more people would opt for outside options such as transit for their journeys under the optimal parking space allocation plan than under the benchmark.

4.2.4 Distinct Tourist Coach Sizes

To investigate the impact of different types of coaches on traffic congestion and parking spaces, we conducted a study focusing on products from YUTONG company as an illustrative example (YUTONG, 2019). We selected four distinct types of coaches, each varying in seat capacity and length, to assess their effects on traffic. The findings of our study are presented in Table 6.

Table 6 The comparison between different types of tourist coaches in terms of β and θ

Vehicle model	Seat	Length (m)	β	θ	Capacity transform (%)	Improvement in obj value (%)	Reduction in CO_2 (%)
C13PRO	55	13	2.5	3	1	0	0

C11	51	11	2.1	2.2	1.0784	4.19	0.64
C9	37	9	2	2	1.4865	-0.18	-0.77
D7	25	7	1.2	1.5	2.2	-2	-1.95

The first column represents the specific coach types under consideration. Parameters β and θ are calculated using the data of vehicular emission and length in (YUTONG, 2019). The sixth column showcases the capacity transformation rate for each coach type, using the "C13PRO" type as the benchmark. This rate can be interpreted as the number of coaches required when transporting 55 people, with the C13PRO type requiring one coach while the D7 type requiring 2.2 coaches, and so forth. This rate is obtained by dividing the number of seats in each coach type by the number of seats in the C13PRO type. The seventh and eighth columns show the improvement in total cost and the reduction in CO_2 emission respectively.

The results of our study shed light on the fact that choosing the appropriate type of tourist coach can play a significant role in mitigating traffic congestion and emissions, particularly during peak tourism seasons. This is because different types of coaches have distinct characteristics that can impact traffic flow. On one hand, larger coaches have a higher seat capacity, allowing them to transport more people at once. However, their larger size and weight can result in lower speeds while traveling. This reduced speed can contribute to congestion, especially in areas with limited road capacity or heavy traffic. On the other hand, smaller coaches may be more nimble and able to navigate through traffic more easily. They can maneuver through narrower streets and congested areas more efficiently, potentially reducing the accumulation of vehicles in a given zone. However, if there is a high demand for transportation and a larger number of smaller coaches are used, this can lead to additional accumulations, causing congestion in certain areas.

Therefore, finding the right balance between capacity and maneuverability is crucial. Opting for a reasonable type of tourist coach that strikes a balance between capacity and flexibility can help minimize congestion during tourism seasons. This requires considering factors such as the anticipated number of passengers, road conditions, and the specific characteristics of the area where the coaches will operate. In this study, we find that C11 is the optimal type of tourist coach bus for Hong Kong as it leads to the minimum overall cost and emissions.

4.2.5 Distinct Modal Choice

In this subsection, we examine how the mode choice of Class A travelers influences parking allocation plans and the resulting network equilibrium. Recall that Class A travelers can choose between private cars and alternative transportation modes depending on their travel times. To modify the trip demand for private vehicles, we vary the cost of the outside option

in the logit model (3.2.1), where a higher value indicates greater resistance to using alternative transportation modes.

Figure 27 illustrates the relationship between the total travel cost of vehicles and the proportion of private car flow, as affected by varying the parameter c_w^0 in the logit model (3.2.1). By adjusting c_w^0, we observe shifts in the share of private car flow ranging from 0.3 to 0.9. A smaller c_w^0 value corresponds to a decreased travel cost for outside options, leading to more Class A travelers selecting alternative modes of transport (e.g., walking, transit, etc.). Consequently, the optimal allocation of parking spaces to private vehicles also decreases in response to the diminished travel demand, and the travel speed of the entire transportation network improves (Figure 28). This outcome uncovers the intricate relationship among the cost of outside options, travelers' mode choices, and parking allocation strategies. It demonstrates that as the cost of outside options decreases (e.g., through improved transit service), regulatory policies (i.e., parking space allocation strategies) should be adjusted dynamically to encourage the use of such modes so that the benefits of improved outside options in congestion mitigation can be fully exploited.

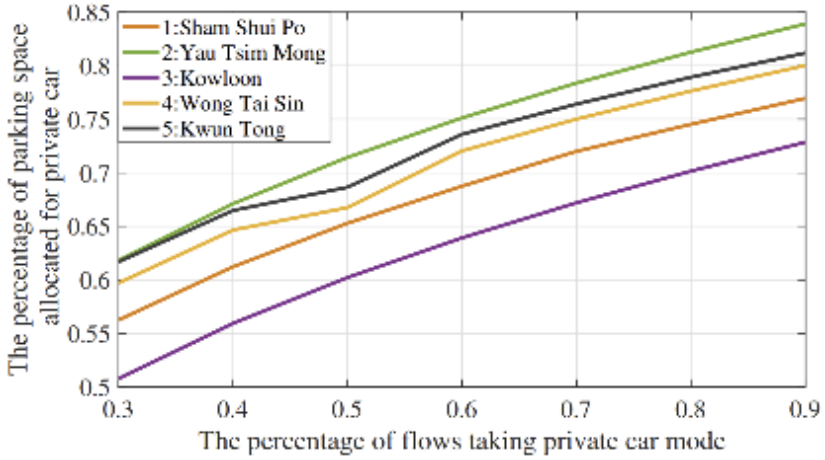

Figure 27 Parking spaces provisions in each sub-zone

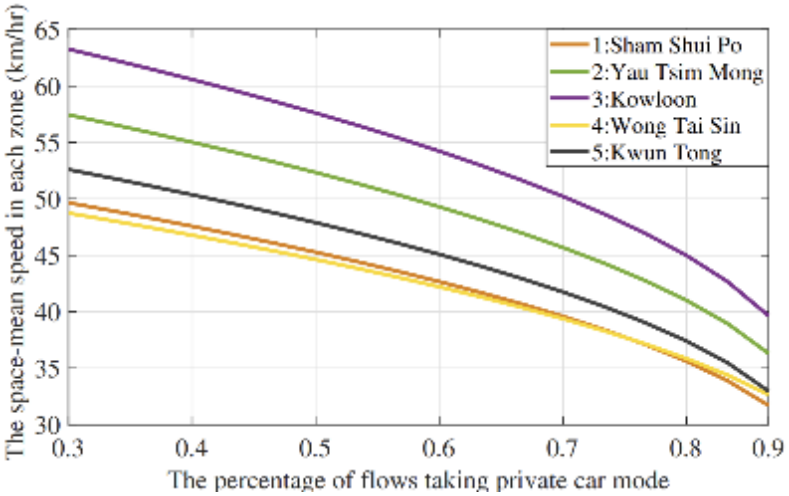

Figure 28 The total travel time of vehicles under different percentages of private car flows

Chapter 5. Policy Implication and Recommendations

The research findings of this project underscore the urgency for the Hong Kong government to implement targeted policies to alleviate congestion caused by tourist-related traffic. These policies should focus on several key areas, including: (1) optimizing short-term passenger pickup and drop-off practices to enhance traffic flow; (2) strategically allocating parking spaces between private vehicles and tourist coaches; (3) managing the traffic considering the interaction between tourist coaches, private vehicles, and public transport service; and (4) supporting data collection and developing advanced information technology systems for real-time tourism-related traffic management. We discuss the details of this policy implications and recommendations in the remainder of this chapter.

5.1 Strategic Implementation of No-Stopping Restrictions (NSRs)

Tourist coaches often park curbside for brief periods to pick up or drop off passengers. Despite the brevity of each stop, the frequent interruptions caused by these buses, compounded by the large space they occupy during these times, disrupt overall traffic flow and have led to significant complaints from local residents, especially in the narrow streets of tourist hotspots like To Kwa Wan and Tsim Sha Tsui. Therefore, the strategic implementation of no-stopping restrictions and clear guidance on designated pickup and drop-off locations is crucial to mitigate the negative impacts caused by the uncoordinated behavior of tourist coaches.

Our results indicate that the implementation of strategically placed no-stopping restrictions (NSRs) and allowable pickup and dropoff locations could be an effective approach to manage tourism-related traffic in urban areas. We have demonstrated that, compared to unregulated scenarios, our proposed modeling framework can guide government agencies in enforcing no-stopping restrictions, resulting in a total travel time reduction of 4.5% in Tsim Sha Tsui and 4.8% in To Kwa Wan. This approach underscores the importance of systematic traffic management through carefully planned restrictions. Crucially, the determination of no-stopping zones should be based on scientific evidence, and the decisions should depend on traffic flows of private vehicles and tourist coaches, link capacity and performance, as well as route choices and traffic flow across the transportation network. When making relevant policies for the setup of no-stopping restrictions and the selection of allowable pickup and drop-off locations, these factors must be carefully considered. We recommend that government to apply the mathematical framework proposed by our project to derive optimal strategies that determines the placement of non-stopping restrictions and allowable pickup and dropoff locations for congestion mitigation. The detailed results regarding the selection of no-stopping restrictions and the selection of allowable pickup and drop-off locations for Tsim Sha Tsui and To Kwa Wan are shown in Figure 16 and Figure 17, respectively.

To ensure effective enforcement of the previously mentioned no-stopping restrictions, it is crucial for the government to implement clear and comprehensive signage systems for tourist coaches. These signs should clearly indicate the areas where stopping is prohibited and direct drivers to designated alternative pickup and drop-off points, thereby minimizing unnecessary cruising that contributes to traffic congestion. Additionally, the deployment of real-time monitoring systems, such as video cameras, is essential to deter and detect violations of parking restrictions. Concurrently, police patrols should be increased in tourist hotspots and areas with no-stopping restrictions to ensure strict compliance with the law. Implementing these measures will safeguard critical junctions and high-traffic corridors, while promoting the efficient movement of tourist coaches through well-planned alternative stopping points.

5.2 Optimizing Parking Space Allocation between Tourist Coaches and Private Vehicles

Aside from requiring short-term curbside parking for passenger pickup and dropoff, tourist coaches also need off-street parking for extended periods between trips. However, because these vehicles require significantly larger parking spaces and given the severe limitation on land in Hong Kong, there is a notable shortage of off-road parking spaces for tourist coaches. While it might be suggested to create new parking areas for these coaches, our project recommends that the government should reconsider the allocation of existing parking spaces between private vehicles and tourist coaches. This approach is more feasible in Hong Kong, especially since converting existing parking spaces from private vehicle use to tourist coach use is generally easier and more practical than creating new parking areas.

This project investigated the optimal proportion of parking space allocation for tourist coaches versus private vehicles in various areas of the city. Specifically, we divided the entire Kowloon region into several districts, including Yau Tsim Mong, Sham Shui Po, Kowloon City, Wong Tai Sin, and Kwun Tong. For each district, we identified the appropriate proportion of spaces that should be allocated to private vehicles versus tourist coaches. Our research demonstrates that compared to the current allocation of parking spaces, a slight adjustment in the ratios of parking spaces allocated to tourist coaches and private vehicles can significantly improve overall traffic performance. In particular, the recommendations for optimal parking space allocation are shown in Figure 24. Compared to the status quo, the recommended parking space provision has led to a 4.2% reduction in private car cruising time and a 23.3% reduction in cruising time for tourist coaches, contributing to an overall 7.8% decrease in cruising time.

We recommend that relevant agencies use the proposed mathematical model to guide the

planning of parking spaces for both tourist coaches and private vehicles. This model offers optimal parking space provision strategies which depend on various factors including the spatial distribution of travel demand for private vehicles, the modal split between private vehicles and public transport services within the multimodal transportation network, and zonal-level macroscopic fundamental diagrams that characterize the average congestion of the zone as a function of vehicle accumulation. It will offer evidence-based policy guidance for the optimal use of land spaces to improve traffic performance and mitigate the negative externalities caused by tourist coaches.

5.3 Jointly Considering Provision of Parking Space and the Provision of Public Transport Services

The travel behaviors, such as mode and route choices, have a significant impact on both the traffic flow over the transportation network and the environmental effects associated with travelers. In densely populated cities like Hong Kong, public transit should play a pivotal role in the multimodal transportation system due to its efficiency in terms of space utilization and environmental footprint. However, tourist groups visiting Hong Kong often rely on transportation services provided by tourist coaches, as organizing public transit for large groups can be challenging. In contrast, local residents traveling by private vehicles enjoy greater flexibility, and thus, transit should be promoted as the primary mode to enhance efficiency. In this regard, we recommend that when the government formulates policies to determine the parking provisions for tourist coaches and private vehicles, it should also consider how these provisions influence the mode choices of private vehicle passengers. Understanding this influence is crucial for developing planning strategies that encourage the adoption of public transportation. This holistic approach to policy-making will not only address parking needs but also promote more sustainable transportation choices, benefiting both traffic flow and environmental quality.

The policy recommendations outlined above are supported by the results of numerical studies conducted in Kowloon. These results indicate that optimal parking provisions for tourist coaches and private vehicles are not merely a function of their respective traffic flow proportions. Instead, parking spaces allocated to tourist coaches in each city zone typically exceed their share of overall traffic. This strategy increases the cost of finding parking for private vehicles, thereby encouraging some private vehicle users to switch to public transit. However, it is crucial to maintain this priority within an appropriate range to avoid excessively raising the overall travel costs for private vehicle passengers, which could lead to additional concerns. The proposed mathematical framework provides a methodical way to balance traffic congestion, the costs incurred by private vehicle passengers, and the expenses

faced by tourists. We recommend that relevant government agencies adopt this framework to formulate evidence-based policies that achieve this balance effectively.

5.4 Supporting Data Collection and Development of Information Technology Systems for Real-time Congestion Management

We recommend that the government support enhanced data collection, particularly concerning tourist coaches. The data should capture not only the seasonal spatial and temporal distribution of tourist coach traffic but should also ideally reflect real-time fluctuations within a day, such as hour-to-hour traffic demand variations. In this project, we collected data on the traffic flow of tourist coach buses in To Kwa Wan during peak hours, which has proven crucial for calibrating model parameters to inform optimal policy decisions. Such data collection efforts should be further supported at an expanded range, e.g., across the entire city, either through manual counts at specific locations or by adopting more advanced methods, such as installing GPS units on tourist coaches to track their trajectories in real time. This information is invaluable not only for devising long-term optimal parking provision strategies but also for enabling more flexible transportation policies concerning non-stopping restrictions and the selection of permissible pickup and drop-off locations. For example, by utilizing real-time GPS data from tourist coaches, the planner can dynamically adjust the locations of no-stopping restrictions and designated pickup and drop-off points in response to changes in traffic congestion throughout the day. This enables dynamic and advanced management of tourism traffic, which will significantly improve overall traffic performance across the transportation network.

We also recommend supporting the development of information and technology systems to proactively manage the travel choices of tourists and tourist coaches for congestion mitigation. Currently, when allocating parking spaces, establishing no-stopping restrictions, and selecting allowable pickup and drop-off locations, policymakers typically adopt a passive approach. They treat travel demand as a given and then try to optimize resource use to accommodate this demand as efficiently as possible. However, the travel demand of tourist coaches possesses significant flexibility. Specifically, the timing and destinations of visits can be adjusted freely based on real-time congestion information at each tourist hotspot. This flexibility holds substantial potential for mitigating traffic congestion but remains untapped due to the absence of an information and technology system that collects real-time data, informs tourist coach drivers about congestion conditions, and suggests optimal routes and itinerary choices. Therefore, we recommend developing an information and technology system that can offer personalized recommendations to individual tourist coach drivers by planning their daily itineraries to prevent congestion from large groups converging on the same location simultaneously. This system should be based on real-time data collection and

capable of displaying congestion information and suggesting intelligent itinerary plans. Implementing such a system will transform traditional tourism management strategies from a passive resource provision approach based on predetermined demand to a proactive approach where demand is shaped by the information and technology systems.

Chapter 6. Conclusions

This research project addresses two critical aspects of urban traffic management: the regulation of curbside pickup and drop-off activities by tourist coaches (Task I) and the optimization of hourly parking provision for tourist coaches (Task II). These complementary investigations provide comprehensive insights into managing tourist coach operations within complex urban environments.

Task I presents a mathematical framework for setting up the No-Stop Regulations (NSRs) distribution in urban networks, focusing on the delicate balance between tourist coach operations and private car traffic. The intellectual core of this part lies in the formulation of the NSR optimization problem as a bi-level mixed integer program with equilibrium constraints. This formulation elegantly captures the hierarchical nature of the problem, with the upper level representing governmental decision-making for NSR placement to minimize total network travel time, while the lower level models the equilibrium behavior of both private cars and tourist coaches under these regulations.

To address the computational challenges inherent in this complex optimization problem, we developed a sophisticated outer approximation (OA) algorithm enhanced with several innovative features. These improvements include the linearization of the objective function and conditional constraints in the master problem, transforming it into a more tractable single-level mixed integer linear problem. The algorithm's efficiency was further enhanced through the implementation of a demand-shifting procedure for calibrating different demand states under given destinations, and various acceleration techniques including the tightening of feasible regions for integer variables and the introduction of link thresholds in each iteration.

The practical applicability of this methodology was demonstrated through two real-world case studies in Hong Kong, specifically in Tsim Sha Tsui and To Kwa Wan. The implementation yielded impressive results, achieving a 12-17% reduction in total travel time compared to scenarios without NSRs in both locations. The algorithm demonstrated remarkable efficiency, particularly in obtaining the upper bound within the first iteration, an attribute likely due to the high private car demand in the areas studied. The success of this

approach in such complex urban environments confirms its potential as a valuable tool for urban planning and traffic management.

Task II shifts focus to the crucial issue of parking space provision, presenting a comprehensive analysis of how parking allocation for private cars and tourist coaches influences traffic congestion. The research introduces a novel zonal-level spatial equilibrium model that captures the distribution patterns of both transportation modes, their cruising-for-parking behaviors, and the resulting traffic congestion across different sub-zones of the city. The incorporation of the macroscopic fundamental diagram (MFD) proves particularly valuable in characterizing the joint impacts of private cars and tourist coaches on aggregate traffic congestion. The model is structured as a two-layer optimization program, with the upper layer focusing on optimal parking space allocation to minimize total social costs, while the lower layer manages traffic flow distribution to achieve user equilibrium conditions. This approach enables quantification of the negative impacts of cruising-for-parking behaviors on traffic flow and provides optimal parking capacity recommendations for each sub-zone to minimize congestion externalities under user equilibrium conditions.

The findings reveal that parking space allocation significantly influences both traffic flow and cruising-for-parking time, with varying effects across different urban contexts. Specifically, we divided the entire Kowloon region into several districts, including Yau Tsim Mong, Sham Shui Po, Kowloon City, Wong Tai Sin, and Kwun Tong. For each district, we identified the appropriate proportion of spaces that should be allocated to private vehicles versus tourist coaches. Our research demonstrates that compared to the current allocation of parking spaces, a slight adjustment in the ratios of parking spaces allocated to tourist coaches and private vehicles can significantly improve overall traffic performance. Compared to the status quo, the recommended parking space provision has led to a 4.2% reduction in private car cruising time and a 23.3% reduction in cruising time for tourist coaches, contributing to an overall 7.8% decrease in cruising time.

This comprehensive study provides valuable insights for transportation planners and policymakers, emphasizing the critical role of both NSR placement and parking space allocation in optimizing urban transportation system performance. The developed methodologies and findings offer practical tools and guidelines for improving traffic flow, reducing cruising-for-parking time, and minimizing overall travel time in complex urban environments. The success of these approaches in addressing real-world challenges demonstrates their potential for broader application in urban transportation planning and management.

Chapter 7. Public Dessemination

This research was presented at the World Transport Convention on 2024.06.26 - 2024.06.29. Our presentation is titled as “Optimal Parking Provision for Tourist Coaches in Bi Modal Urban Transportation Networks”. The World Transport Convention (WTC), inaugurated in 2017, is a prestigious international conference and exhibition platform in the transportation sector. Approved by the State Council of China, it is jointly hosted by the China Association for Science and Technology (CAST), the Ministry of Transport, and the Chinese Academy of Engineering (CAE), organized by China Highway & Transportation Society (CHTS), and supported by numerous domestic and international transportation science and technology organizations. WTC holds profound significance in enhancing China's transportation development capabilities and steering the future direction of global transportation development. As an international platform for the transportation industry, WTC continues to evolve and advance, establishing itself as a truly influential global transportation forum.

This research project was featured in dotdotnews.com on May 10, 2024. The article, titled "Mitigating Traffic Congestion Caused by Tourist Coaches in Hong Kong," succinctly outlines the major objective of the project and addresses several crucial questions related to it, including: (1) the relevance of the proposed research to public policy making in Hong Kong; (2) the primary goal of the research; and (3) the benefits of the research. The article can be found in the reference section of this report (Li and Lo, 2024).

This research project was also featured on wenweipo.com on September 21, 2024. The article, titled "Congestion Mitigation for Tourist Coach Buses Based on Artificial Intelligence," highlighted the major outcomes of this project. It mentioned that the research team was supported by the Public Policy Research Funding Scheme to develop a model that analyzes optimal regulatory policies for mitigating congestion caused by tourist coaches. Additionally, the article emphasized the benefits of reallocating some parking spaces from private vehicles to tourist coaches, which helps reduce the cruising traffic of these coaches and thus improves the overall efficiency of the transportation network. The article can be found in the reference section of this report (Wen, 2024).

References

Abdulaal, M., LeBlanc, L.J., 1979. Continuous equilibrium network design models. Transp. Res. Part B Methodol. 13, 19–32.

An, K., Lo, H.K., 2016. Two-phase stochastic program for transit network design under demand uncertainty. Transp. Res. Part B Methodol. 84, 157–181.

An, K., Lo, H.K., 2015. Robust transit network design with stochastic demand considering development density. Transp. Res. Part B Methodol. 81, 737–754.

Anderson, S.P., De Palma, A., 2004. The economics of pricing parking. J. Urban Econ. 55, 1–20.

Arnott, R., Inci, E., 2006a. An integrated model of downtown parking and traffic congestion. J. Urban Econ. 60, 418–442.

Arnott, R., Inci, E., 2006b. An integrated model of downtown parking and traffic congestion. J. Urban Econ. 60, 418–442.

Arnott, R., Rowse, J., 1999. Modeling parking. J. Urban Econ. 45, 97–124.

Board, H.K.T., 2021. Fast facts about Hong Kong Tourism.

Bouchard, R.J., Pyers, C.E., 1965a. Use of gravity model for describing urban travel. Highw. Res. Rec. 88, 5.

Bouchard, R.J., Pyers, C.E., 1965b. Use of gravity model for describing urban travel. Highw. Res. Rec. 88, 5.

Boyles, S.D., Tang, S., Unnikrishnan, A., 2015. Parking search equilibrium on a network. Transp. Res. Part B Methodol. 81, 390–409.

Brands, T., Van Berkum, E.C., 2014. Performance of a genetic algorithm for solving the multi-objective, multimodel transportation network design problem. Int. J. Transp. 2, 1–20.

Buisson, C., Ladier, C., 2009. Exploring the impact of homogeneity of traffic measurements on the existence of macroscopic fundamental diagrams. Transp. Res. Rec. 2124, 127–136.

Cantarella, G.E., Vitetta, A., 2006. The multi-criteria road network design problem in an urban area. Transportation 33, 567–588.

Cao, J., Menendez, M., 2015a. System dynamics of urban traffic based on its parking-related-states. Transp. Res. Part B Methodol. 81, 718–736.

Cao, J., Menendez, M., 2015b. System dynamics of urban traffic based on its parking-related-states. Transp. Res. Part B Methodol. 81, 718–736.

Chen, Z., Spana, S., Yin, Y., 2019. An advanced parking navigation system for downtown parking.

Chiou, S.-W., 2016. A robust urban traffic network design with signal settings. Inf. Sci. 334,

144–160.

City of Brussels, 2022. Touristic coach parking.

Convention and Visitors Bureau, 2022. Motorcoach traffic and parking.

Daganzo, C.F., 2007. Urban gridlock: Macroscopic modeling and mitigation approaches. Transp. Res. Part B Methodol. 41, 49–62.

Daganzo, C.F., Geroliminis, N., 2008. An analytical approximation for the macroscopic fundamental diagram of urban traffic. Transp. Res. Part B Methodol. 42, 771–781.

Dantsuji, T., Fukuda, D., Zheng, N., 2021. Simulation-based joint optimization framework for congestion mitigation in multimodal urban network: a macroscopic approach. Transportation 48, 673–697.

Di, Z., Yang, L., Qi, J., Gao, Z., 2018. Transportation network design for maximizing flow-based accessibility. Transp. Res. Part B Methodol. 110, 209–238.

Diehl, C., Ranjbari, A., Goodchild, A., 2021. Curbspace management challenges and opportunities from public and private sector perspectives. Transp. Res. Rec. 2675, 1413–1427.

Du, Y., Yu, S., Meng, Q., Jiang, S., 2019. Allocation of street parking facilities in a capacitated network with equilibrium constraints on drivers' traveling and cruising for parking. Transp. Res. Part C Emerg. Technol. 101, 181–207.

Fan, W., Machemehl, R.B., 2006. Optimal transit route network design problem with variable transit demand: genetic algorithm approach. J. Transp. Eng. 132, 40–51.

Farahani, R.Z., Miandoabchi, E., Szeto, W.Y., Rashidi, H., 2013. A review of urban transportation network design problems. Eur. J. Oper. Res. 229, 281–302.

Farvaresh, H., Sepehri, M.M., 2013. A branch and bound algorithm for bi-level discrete network design problem. Netw. Spat. Econ. 13, 67–106.

Fontaine, P., Minner, S., 2014. Benders decomposition for discrete-continuous linear bilevel problems with application to traffic network design. Transp. Res. Part B Methodol. 70, 163–172.

Fragkos, I., Cordeau, J.-F., Jans, R., 2021. Decomposition methods for large-scale network expansion problems. Transp. Res. Part B Methodol. 144, 60–80.

Gao, Z., Sun, H., Zhang, H., 2007. A globally convergent algorithm for transportation continuous network design problem. Optim. Eng. 8, 241–257.

Gayah, V.V., Daganzo, C.F., 2011. Clockwise hysteresis loops in the macroscopic fundamental diagram: an effect of network instability. Transp. Res. Part B Methodol. 45, 643–655.

Gayah, V.V., Dixit, V.V., 2013. Using mobile probe data and the macroscopic fundamental diagram to estimate network densities: Tests using microsimulation. Transp. Res. Rec. 2390, 76–86.

Geroliminis, N., 2015a. Cruising-for-parking in congested cities with an MFD representation. Econ. Transp. 4, 156–165.

Geroliminis, N., 2015b. Cruising-for-parking in congested cities with an MFD representation. Econ. Transp. 4, 156–165.

Geroliminis, N., Boyacı, B., 2012. The effect of variability of urban systems characteristics in the network capacity. Transp. Res. Part B Methodol. 46, 1607–1623.

Geroliminis, N., Daganzo, C.F., 2008a. Existence of urban-scale macroscopic fundamental diagrams: Some experimental findings. Transp. Res. Part B Methodol. 42, 759–770.

Geroliminis, N., Daganzo, C.F., 2008b. Existence of urban-scale macroscopic fundamental diagrams: Some experimental findings. Transp. Res. Part B Methodol. 42, 759–770.

Geroliminis, N., Sun, J., 2011. Properties of a well-defined macroscopic fundamental diagram for urban traffic. Transp. Res. Part B Methodol. 45, 605–617.

Geroliminis, N., Zheng, N., Ampountolas, K., 2014. A three-dimensional macroscopic fundamental diagram for mixed bi-modal urban networks. Transp. Res. Part C Emerg. Technol. 42, 168–181.

Godfrey, J., 1969. The mechanism of a road network. Traffic Eng. Control 8.

Gokalp, C., Patil, P.N., Boyles, S.D., 2021. Post-disaster recovery sequencing strategy for road networks. Transp. Res. Part B Methodol. 153, 228–245.

Gu, W., Cassidy, M.J., Gayah, V.V., Ouyang, Y., 2013. Mitigating negative impacts of near-side bus stops on cars. Transp. Res. Part B Methodol. 47, 42–56.

Gu, Z., Najmi, A., Saberi, M., Liu, W., Rashidi, T.H., 2020. Macroscopic parking dynamics modeling and optimal real-time pricing considering cruising-for-parking. Transp. Res. Part C Emerg. Technol. 118, 102714.

HKSAR, 2019. LCQ12: Mitigation measures to tackle impact by visitors to Hong Kong on local community.

Hosseininasab, S.-M., Shetab-Boushehri, S.-N., 2015. Integration of selecting and scheduling urban road construction projects as a time-dependent discrete network design problem. Eur. J. Oper. Res. 246, 762–771.

Idris, Mohd, Y., 2009. Parking guidance system utilizing wireless sensor network and ultrasonic sensor. Inf. Technol. J.

Ingole, D., Mariotte, G., Leclercq, L., 2020. Perimeter gating control and citywide dynamic user equilibrium: A macroscopic modeling framework. Transp. Res. Part C Emerg. Technol. 111, 22–49.

Jaller, M., 2021. Curbside Management Is Critical for Minimizing Emissions and Congestion.

Jaller, M., Rodie, C., Zhang, M., Lin, H., Lewis, K., others, 2021. Fighting for curb space: Parking, ride-hailing, urban freight deliveries, and other users.

Juan, W., Huapu, L., Xinxin, Y., Changzhi, B., 2012. Genetic algorithm for multiuser discrete

network design problem under demand uncertainty. Math. Probl. Eng. 2012, 686272.

Khisty, C.J., Lall, B.K., 2016a. Transportation engineering. Pearson Education India.

Khisty, C.J., Lall, B.K., 2016b. Transportation engineering. Pearson Education India.

Knoop, V.L., Hoogendoorn, S., Van Lint, J., 2013. The impact of traffic dynamics on macroscopic fundamental diagram, in: 92nd Annual Meeting Transportation Research Board, Washington, USA, 13-17 January 2013; Authors Version. Transportation Research Board.

Leblanc, L.J., 1975. An algorithm for the discrete network design problem. Transp. Sci. 9, 183–199.

Leclercq, L., Chiabaut, N., Trinquier, B., 2014. Macroscopic fundamental diagrams: A cross-comparison of estimation methods. Transp. Res. Part B Methodol. 62, 1–12.

Leclercq, L., Geroliminis, N., 2013. Estimating MFDs in simple networks with route choice. Procedia-Soc. Behav. Sci. 80, 99–118.

Legislative Council HK, 2021. The latest background of parking space supply.

Leurent, F., Boujnah, H., 2014. A user equilibrium, traffic assignment model of network route and parking lot choice, with search circuits and cruising flows. Transp. Res. Part C Emerg. Technol. 47, 28–46.

Li, C., Yang, H., Zhu, D., Meng, Q., 2012. A global optimization method for continuous network design problems. Transp. Res. Part B Methodol. 46, 1144–1158.

Li, L., Lo, H.K., Huang, W., Xiao, F., 2021. Mixed bus fleet location-routing-scheduling under range uncertainty. Transp. Res. Part B Methodol. 146, 155–179.

Li, S., Ju, Y., 2009. Evaluation of bus-exclusive lanes. IEEE Trans. Intell. Transp. Syst. 10, 236–245.

Li, S., Lo, H.K., 2024. Mitigating traffic congestion caused by tourist coaches in Hong Kong. https://www.dotdotnews.com/a/202405/10/AP663defc6e4b096780aa43041.html.

Li, S., Qin, J., Yang, H., Poolla, K., Varaiya, P., 2020. Off-Street Parking for TNC Vehicles to Reduce Cruising Traffic, in: 2020 59th IEEE Conference on Decision and Control (CDC). IEEE, pp. 2585–2590.

Liang, J., Wu, J., Gao, Z., Sun, H., Yang, X., Lo, H.K., 2019. Bus transit network design with uncertainties on the basis of a metro network: A two-step model framework. Transp. Res. Part B Methodol. 126, 115–138.

Liu, J., Ma, W., Qian, S., 2023. Optimal curbside pricing for managing ride-hailing pick-ups and drop-offs. Transp. Res. Part C Emerg. Technol. 146, 103960.

Liu, J., Zhou, X., 2016. Capacitated transit service network design with boundedly rational agents. Transp. Res. Part B Methodol. 93, 225–250.

Liu, W., 2018. An equilibrium analysis of commuter parking in the era of autonomous vehicles. Transp. Res. Part C Emerg. Technol. 92, 191–207.

Liu, W., Geroliminis, N., 2016. Modeling the morning commute for urban networks with cruising-for-parking: An MFD approach. Transp. Res. Part B Methodol. 93, 470–494.

Liu, X., Xu, L., Qian, S., Ma, W., 2020. A Data-Driven Approach to Manage the Curbside Ride-hailing Pick-ups and Drop-offs, in: ISTDM 2021.

Loder, A., Ambühl, L., Menendez, M., Axhausen, K.W., 2019. Understanding traffic capacity of urban networks. Sci. Rep. 9, 16283.

Loder, A., Ambühl, L., Menendez, M., Axhausen, K.W., 2017. Empirics of multi-modal traffic networks–Using the 3D macroscopic fundamental diagram. Transp. Res. Part C Emerg. Technol. 82, 88–101.

Loder, A., Bliemer, M.C., Axhausen, K.W., 2022. Optimal pricing and investment in a multi-modal city—Introducing a macroscopic network design problem based on the MFD. Transp. Res. Part Policy Pract. 156, 113–132.

Luathep, P., Sumalee, A., Lam, W.H., Li, Z.-C., Lo, H.K., 2011. Global optimization method for mixed transportation network design problem: a mixed-integer linear programming approach. Transp. Res. Part B Methodol. 45, 808–827.

Luthy, N., Guler, S.I., Menendez, M., 2016. Systemwide effects of bus stops: bus bays vs. curbside bus stops.

Ma, Q., Kockelman, K., Segal, M., 2018. Making the most of curb spaces in a world of shared autonomous vehicles: a case study of Austin, Texas.

Mahmassani, H., Williams, J.C., Herman, R., 1987. Performance of urban traffic networks, in: Proceedings of the 10th International Symposium on Transportation and Traffic Theory. Elsevier Amsterdam, The Netherlands, pp. 1–20.

Mahmassani, H.S., Saberi, M., Zockaie, A., 2013. Urban network gridlock: Theory, characteristics, and dynamics. Procedia-Soc. Behav. Sci. 80, 79–98.

Mahmoudi, R., Shetab-Boushehri, S.-N., Hejazi, S.R., Emrouznejad, A., Rajabi, P., 2019. A hybrid egalitarian bargaining game-DEA and sustainable network design approach for evaluating, selecting and scheduling urban road construction projects. Transp. Res. Part E Logist. Transp. Rev. 130, 161–183.

Manual, H.C., 2000. Highway capacity manual. Wash. DC 2.

Martens, K., Benenson, I., Levy, N., 2010a. The dilemma of on-street parking policy: exploring cruising for parking using an agent-based model, in: Geospatial Analysis and Modelling of Urban Structure and Dynamics. Springer, pp. 121–138.

Martens, K., Benenson, I., Levy, N., 2010b. The dilemma of on-street parking policy: exploring cruising for parking using an agent-based model, in: Geospatial Analysis and Modelling of Urban Structure and Dynamics. Springer, pp. 121–138.

Millard-Ball, A., Liu, L., Hansen, W., Cooper, D., Castiglione, J., 2023. Where Ridehail Drivers Go Between Trips. Transportation 50, 1959–1981.

Mohebifard, R., Hajbabaie, A., 2019. Optimal network-level traffic signal control: A benders decomposition-based solution algorithm. Transp. Res. Part B Methodol. 121, 252–274.

news.gov.hk, 2013. Coach parking spaces.

Ng, M.T., Mahmassani, H.S., Verbas, Ö., Cokyasar, T., Engelhardt, R., 2024. Redesigning large-scale multimodal transit networks with shared autonomous mobility services. Transp. Res. Part C Emerg. Technol. 104575.

Nie, Y., Zhang, H.M., 2010. Solving the dynamic user optimal assignment problem considering queue spillback. Netw. Spat. Econ. 10, 49–71.

Nieto-Isaza, S., Fontaine, P., Minner, S., 2022. The value of stochastic crowd resources and strategic location of mini-depots for last-mile delivery: A Benders decomposition approach. Transp. Res. Part B Methodol. 157, 62–79.

Nourinejad, M., Wenneman, A., Habib, K.N., Roorda, M.J., 2014. Truck parking in urban areas: Application of choice modelling within traffic microsimulation. Transp. Res. Part Policy Pract. 64, 54–64.

Ntziachristos, L., Gkatzoflias, D., Kouridis, C., Samaras, Z., 2009. COPERT: a European road transport emission inventory model, in: Information Technologies in Environmental Engineering: Proceedings of the 4th International ICSC Symposium Thessaloniki, Greece, May 28-29, 2009. Springer, pp. 491–504.

Planning Department, 2018. Internal transport facilities.

Poorzahedy, H., Turnquist, M.A., 1982. Approximate algorithms for the discrete network design problem. Transp. Res. Part B Methodol. 16, 45–55.

Qian, Z., Rajagopal, R., 2015. Optimal dynamic pricing for morning commute parking. Transp. Transp. Sci. 11, 291–316.

Qian, Z.S., Xiao, F.E., Zhang, H., 2012. Managing morning commute traffic with parking. Transp. Res. Part B Methodol. 46, 894–916.

Saberi, M., Mahmassani, H.S., 2012. Exploring properties of networkwide flow–density relations in a freeway network. Transp. Res. Rec. 2315, 153–163.

Shalaby, A.S., 1999. Simulating performance impacts of bus lanes and supporting measures. J. Transp. Eng. 125, 390–397.

Shao, C., Yang, H., Zhang, Y., Ke, J., 2016. A simple reservation and allocation model of shared parking lots. Transp. Res. Part C Emerg. Technol. 71, 303–312.

Sheffi, Y., 1985. Urban transportation networks. Prentice-Hall, Englewood Cliffs, NJ.

Shoup, D.C., 2021. The high cost of free parking. Routledge.

Shoup, D.C., 2006. Cruising for parking. Transp. Policy 13, 479–486.

Su, X., Sun, F., Ng, N., 2018. Relief in sight for long-suffering residents of Hong Kong's crowded Kowloon City as officials pledge tourist curbs to ease chaos. South China

Morning Post.

Sun, Z., 2016. Continuous transportation network design problem based on bi-level programming model. Procedia Eng. 137, 277–282.

Szeto, W.Y., Jiang, Y., Wang, D., Sumalee, A., 2015. A sustainable road network design problem with land use transportation interaction over time. Netw. Spat. Econ. 15, 791–822.

Tang, Z.-Y., Tian, L.-J., Wang, D.Z., 2021. Multi-modal morning commute with endogenous shared autonomous vehicle penetration considering parking space constraint. Transp. Res. Part E Logist. Transp. Rev. 151, 102354.

Transport Department HK, 2024. Traffic data strategic major roads.

Transport Department HK, 2011. Travel Characteristics Survey (2011).

Transport for London, 2022. Special parking arrangements.

Wang, D.Z., Liu, H., Szeto, W.Y., 2015. A novel discrete network design problem formulation and its global optimization solution algorithm. Transp. Res. Part E Logist. Transp. Rev. 79, 213–230.

Wang, G., Gao, Z., Xu, M., Sun, H., 2014. Models and a relaxation algorithm for continuous network design problem with a tradable credit scheme and equity constraints. Comput. Oper. Res. 41, 252–261.

Wang, J., Zhang, X., Wang, H., Zhang, M., 2019. Optimal parking supply in bi-modal transportation network considering transit scale economies. Transp. Res. Part E Logist. Transp. Rev. 130, 207–229.

Wang, S., Meng, Q., Yang, H., 2013. Global optimization methods for the discrete network design problem. Transp. Res. Part B Methodol. 50, 42–60.

Wen, L., 2024. Congestion mitigation for tourist coach buses based on artificial intelligence. https://www.wenweipo.com/a/202409/21/AP66edd833e4b0c180aa950f06.html.

Wong, R., Szeto, W., Wong, S., 2014. Bi-level decisions of vacant taxi drivers traveling towards taxi stands in customer-search: Modeling methodology and policy implications. Transp. Policy 33, 73–81.

World Tourism Organization, 2023. UNWTO World Tourism Barometer.

Xiao, J., 2019. Congestion Mitigation for Planned Special Events: Parking, Ridesharing and Network Configuration. Arizona State University.

Xu, Z., Yin, Y., Zha, L., 2017. Optimal parking provision for ride-sourcing services. Transp. Res. Part B Methodol. 105, 559–578.

Yang, H., H. Bell, M.G., 1998. Models and algorithms for road network design: a review and some new developments. Transp. Rev. 18, 257–278.

Yang, H., Huang, H.-J., 2004. The multi-class, multi-criteria traffic network equilibrium and systems optimum problem. Transp. Res. Part B Methodol. 38, 1–15.

Yang, L., Di, Z., Dessouky, M.M., Gao, Z., Shi, J., 2020. Collaborative optimization of last-train timetables with accessibility: A space-time network design based approach. Transp. Res. Part C Emerg. Technol. 114, 572–597.

Yao, J., Shi, F., Zhou, Z., Qin, J., 2012. Combinatorial optimization of exclusive bus lanes and bus frequencies in multi-modal transportation network. J. Transp. Eng. 138, 1422–1429.

Yin, J., Yang, L., Tang, T., Gao, Z., Ran, B., 2017. Dynamic passenger demand oriented metro train scheduling with energy-efficiency and waiting time minimization: Mixed-integer linear programming approaches. Transp. Res. Part B Methodol. 97, 182–213.

Yu, B., Kong, L., Sun, Y., Yao, B., Gao, Z., 2015. A bi-level programming for bus lane network design. Transp. Res. Part C Emerg. Technol. 55, 310–327.

YUTONG, 2019. The products of YUTONG company.

Zaferanieh, M., Abareshi, M., Jafarzadeh, M., 2023. A bi-level p-facility network design problem in the presence of congestion. Comput. Ind. Eng. 176, 109010.

Zhang, F., Liu, W., Wang, X., Yang, H., 2020. Parking sharing problem with spatially distributed parking supplies. Transp. Res. Part C Emerg. Technol. 117, 102676.

Zhang, L., Yang, H., Wu, D., Wang, D., 2014. Solving a discrete multimodal transportation network design problem. Transp. Res. Part C Emerg. Technol. 49, 73–86.

Zhang, X., Yang, H., Huang, H.-J., 2011. Improving travel efficiency by parking permits distribution and trading. Transp. Res. Part B Methodol. 45, 1018–1034.

Zhao, C., Liao, F., Li, X., Du, Y., 2021. Macroscopic modeling and dynamic control of on-street cruising-for-parking of autonomous vehicles in a multi-region urban road network. Transp. Res. Part C Emerg. Technol. 128, 103176.

Zheng, N., Dantsuji, T., Wang, P., Geroliminis, N., 2017. Macroscopic approach for optimizing road space allocation of bus lanes in multimodal urban networks through simulation analysis. Transp. Res. Rec. 2651, 42–51.

Zheng, N., Geroliminis, N., 2016. Modeling and optimization of multimodal urban networks with limited parking and dynamic pricing. Transp. Res. Part B Methodol. 83, 36–58.

Zhu, L., Yu, L., Chen, X.-M., Guo, J.-F., 2012. Simulated analysis of exclusive bus lanes on expressways: case study in Beijing, China. J. Public Transp. 15, 111–128.

Board, H. K. (2021). *Fast facts about Hong Kong Tourism*. Retrieved from https://www.discoverhongkong.com/eng/hktb/newsroom/fast-facts-about-hong-kong-tourism.html

Suand Sun, Fiona and Ng, NaomiXinqi. (2018). Relief in sight for long-suffering residents of Hong Kong’s crowded Kowloon City as officials pledge tourist curbs to ease chaos. 檢索來源：https://www.scmp.com/news/hong-kong/hong-kong-economy/article/2179721/relief-sight-long-suffering-residents-hong-kongs