

Multi-modal user equilibrium and system optimum in urban transport systems including shared mobility services

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1 MULTI-MODAL USER EQUILIBRIUM AND SYSTEM OPTIMUM IN URBAN
  TRANSPORT SYSTEMS INCLUDING SHARED MOBILITY SERVICES
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ABSTRACT

Shared Mobility Services (SMSs) have reshaped urban transportation systems, providing effective and flexible mobility options. As these services can reduce traffic congestion and emissions by reducing the number of cars, they are likely to become an essential part of the urban transportation landscape, which emphasizes the importance of analyzing and understanding their impacts on the system and users' travel choices, especially when integrated with public transport (PT). Most existing works do not consider interactions between SMSs and PT, leading to inaccurate PT and SMS estimates, as in most cases, PT does not cover the first and last mile of journeys. In this study, we first provide a comprehensive literature review on modeling SMSs in multi-modal systems. Then, we present an analytical traffic assignment model formulated as a Mixed-Integer Quadratic 10 Problem, which can be solved with existing solvers. In particular, the proposed model can represent 11 various travel options and any logical combination. We adapt the Beckmann formulation with a 12 link-wise objective function, including time and monetary costs. We perform an in-depth analysis 13 of commuter behavior on two test cases and investigate the difference between user equilibrium 14 and system optimum in such a complex system. 15

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17 Keywords: Shared Mobility Services, Multi-Modal Transportation Network, Intermodality, User

18 Equilibrium, System Optimum.

INTRODUCTION

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With the rapid growth of demand for urban transportation systems, addressing the population's travel needs has become challenging. Because expanding the physical transportation network is not always feasible and beneficial, new mobility services have emerged, transforming and revolutionizing how people move within cities (1). In particular, shared mobility services (SMSs) have 5 gained popularity due to their convenience and cost-effectiveness. By promoting shared mobility and reducing the number of cars in the network, these services have the potential to reduce 7 traffic congestion, minimize emissions, and alleviate parking space demands. Furthermore, SMSs can radically improve mobility, especially in low-demand and low-density regions where public 10 transport (PT) is unable to provide first and last-mile transportation (e.g., from origin to the transportation hub or from the hub to destination) (2).

Shared mobility describes various mobility options. For instance, carpooling is an SMS where commuters with overlapping itineraries and similar schedules share a privately owned car for the trip. In this context, taxi services can be redefined as an on-demand service, called e-hailing, where one commuter requests a driver to travel from his origin to his destination without sharing the car with other passengers. When the sharing is allowed, the service is called ridesharing (3).

Integrating SMSs with PT has shifted traveling behavior and created a more complex multimodal transportation system (4). On the one hand, commuters face mode and route choices, aiming to reduce travel expenses, while on the other hand, the system owners or traffic engineers strive to optimize mobility services and meet demand with minimized overall costs. This needs a complete understanding of the various transportation services accessible and their associated costs.

Numerous studies have focused on modeling multi-modal transportation systems. Recently, many works have incorporated SMSs into their models. However, a less explored aspect concerns modeling and evaluating combinations of multiple mobility options to accomplish one trip (intermodality). Particularly, using SMSs for first and last mile transportation is often not explored. This lack of integration results in inaccurate traffic predictions and planning. Consequently, individuals may not be able to fully optimize their travel choices, leading to potential inefficiencies and higher expenses (5).

Addressing this issue requires the development of comprehensive transportation models that consider all travel options available to commuters. By integrating SMSs and PT into a unified framework and providing accurate information on costs and travel times, commuters can make more optimal decisions, optimizing individual and system travel expenses.

We first conduct a literature review on multi-modal traffic models in this paper. Second, we formulate an analytical model for multi-modal urban transportation networks, considering SMSs and intermodality. For model tractability, we consider a time-independent setting, leading to a non-convex Mixed-Integer Quadratic Program (MIQP) formulation. In this model, commuters can travel with a single mode or use any combination of the travel options. We formulate commuters' travel decisions using two traffic assignment principles: User equilibrium (UE) and system optimum (SO), to represent the two baseline scenarios for the network. In UE, known as the first Wardrop principle (6), every commuter tries to minimize his own cost, and equilibrium is reached when no one is willing to change his choices to achieve lower costs. The second principle of Wardrop is system-oriented and assumes that the system's total cost is minimized (6). We address the equilibrium problem with the Beckmann transformation and prove that the solution is equivalent to the UE. Therefore, formulating other types of equilibria, such as stochastic user equilibrium (SUE), in which commuters are assumed to minimize their perceived travel costs, will be

straightforward (1).

The proposed model enables the investigation of different planning scenarios by providing network traffic distribution. In this study, we perform a comparative analysis of the two equilibria to investigate the impact of intermodality on the transportation system performance. In particular, we compare the system, including PT and SMSs, competing with the cooperative scenario wherein intermodality is allowed.

LITERATURE REVIEW

Most of the studies in the literature addressed the modeling of SMSs, including background traffic, but they mostly did not consider PT (5). (7) proposed a UE framework to analyze congestion effects arising from carpooling and e-hailing services. Similarly, (8) analyzed the efficiency of e-hailing and ridesharing services in reducing traffic congestion. They showed that fleet size is an important factor for ridesharing efficiency due to the congestion effects of empty fleet vehicles. (9) studied the carpooling demand, with the same origin and destination for riders and drivers, under the SUE principle. They showed that carpooling is preferred for long trips.

Some recent works have included both SMSs and PT in their modeling. For example, (10) analyzed the e-hailing and ridesharing pricing strategies in a multi-modal network, considering PT. (11) proposed a UE framework, under time uncertainties, to analyze the commuters' mode and departure time choices. (12) studied the impacts of e-hailing service on the PT demand and usage of personal cars for the city of Amsterdam. They showed that e-hailing could potentially replace private cars and attract PT demand with a larger fleet. (13) modeled the carpooling service in a multi-modal single-region network and proposed two pricing schemes to alleviate traffic congestion. (14) investigated the use of underutilized bus lanes for ridesharing service and its impacts on the solo-pooled rides split. (15) investigated the integration of shared autonomous vehicles into the multi-modal network, considering PT and parking space constraints. All these studies have not considered interactions between SMSs and PT, referred to as intermodality in this paper. This means that, with these models, commuters have single-mode trips and cannot switch modes between their origin and destination. This results in the use of PT and SMSs being under-estimated or over-estimated, as in most cases, PT does not cover the first and last mile of the journey.

Multiple studies have considered intermodality exclusively in the form of Park-and-Ride mode ((16), (17), (18) and (19)). The use of bikes to complete first-mile and last-mile has also been intensively investigated (See e.g., (20) and (21)). However, only a few recent works have targeted intermodality with SMSs and PT. (22) analyzed the competitiveness and complementarity of e-hailing with PT. They showed that fleet size and trip fares impact using e-hailing services as a first-mile/last-mile option. Similarly, (5) investigated the impacts of e-hailing and ridesharing services on PT ridership and showed that ridesharing can be a competitor of PT when low fares are applied. In (1), the authors proposed an SUE multi-modal framework where commuters access metro stations via bus, car, or e-hailing. The mode and path choices are handled by discrete choice models. In (4), commuters can choose inter-modes with solo driving (park-and-ride mode), carpooling, and e-hailing. Travel behavior is modeled via a multi-layer nested logit model. To our knowledge, these two last-mentioned works present the most comprehensive and highly relevant models related to our research. However, the ridesharing service, biking and walking are not modeled. Additionally, to the best of our knowledge, no work has compared and investigated the difference between UE and SO in such a multi-modal complex system.

One of the goals of this study is to fill this research gap by proposing a comprehensive

analytical model for multi-modal transportation systems, integrating SMSs with PT. We propose a combined framework for carpooling, e-hailing and ridesharing, as well as intermodality. We aim to address UE and SO principles in a tractable (analytical) framework. Insights are provided to understand better the impacts of SMSs on PT and commuters' behavior when these latter act for their benefit or the good of the system.

To help position our work and its contribution, we present a characterization of the existing models in the literature in Table 1. The traffic assignment column categorizes the works based on equilibrium principles. Generalized cost presents the terms included in the travel costs: travel time states for in-vehicle time, waiting time for the time spent before the vehicle arrives at the passenger's position, the service time is the time to be matched, to get in and out of the vehicle and the time spent at PT stops, the monetary cost is the cost of fuel and trip fares. Finally, the travel options column denotes the categories of travel modes and their travel options considered in each model. There are four categories: Personal means, Public transport, Shared mobility services, and Intermodality which includes park-and-ride, walking and/or biking combined with PT (W/B), and using SMSs with PT.

We characterized 22 studies in the literature and compared them with our study (the last row in Table 1) to highlight the research gap we are addressing. Hence, the contributions of this paper can be summarized as follows:

- It establishes a comprehensive Mixed-Integer Quadratic Program for multi-modal transportation networks considering personal transportation means (car, walking, and biking), public transport (bus and metro), as well as shared mobility services (carpooling, ridesharing, and e-hailing)
- It explicitly formulates interactions between shared mobility services and public transport regarding congestion effects and intermodality. It also considers park-and-ride mode and the use of walking and biking for first-mile and last-mile transportation.
- It solves the UE and SO problems when the model simultaneously handles mode choice and path choice, and passenger-driver matching.
- The proposed model is used to analyze the behavior of commuters within a transportation network encompassing multiple travel modes.

30 MODEL FORMULATION

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- 31 This section presents the analytical model for multi-modal urban transportation networks consid-
- 32 ering SMSs integrated with PT. To clearly present the model, we first present a simplified version
- 33 without intermodality. Then, we reformulate the model to consider intermodality. The list of
- 34 notations used in this paper is presented in Table 2.

35 Multi-Modal Transportation Network without Intermodality

- 36 Let us consider an urban transportation network represented as a directed graph G(E,A), wherein
- 37 links (A) represent physical routes, and nodes (E) can represent intersections or zones, depending
- 38 on the level of network aggregation. Let $q^{(i,j)}$ be the travel demand between Origin-Destination
- 39 (OD) pair (i, j), $\forall i, j \in E$. This study assumes the demand for each OD pair is given. Commuters
- 40 traveling between (i, j) must simultaneously choose the mode and path. For travel modes, as il-
- 41 lustrated in Figure 1, commuters can take their car and be solo drivers, be a bus or metro (M)
- 42 passenger, carpooling driver (CD), or carpooling passenger (CP) as long as the matching happens,
- e-hailing passenger (EH) or ridesharing passenger (RS) and thus, be matched with a service vehi-

TABLE 1: Comparison of the different studies on modeling of Shared Mobility Services

Stochastic Travel Waiting Service Monetary Car Walking Biking Bus Metro Carpooling E-bailing Staring Ride Park & Stochastic Time Time Cost		<i>A</i>	Traffic Assignment			Gene	Generalized Cost						Travel Options	otions				
User System Stochastic Travel Maiting Maiting Serial bitum Carrel Maiting Biking Biking	Research)						Person	al Means	P	r .		SMSs		Ī	Intermodality	Į.
		User Equilibrium		Stochastic UE	Travel Time	Waiting Time	Service Time	Monetary Cost			Bus			E-hailing	Ride Sharing	Park & Ride	W/B with PT	SMSs with PT
	Di, Xuan and Ban, 2019 (7)	×			×	×		×	×				×	×				
	Beojone et al., 2021 (8)				×	×			×				×					
	Yan et al., 2019 (9)			×	×	×		×	×				*x					
	Zhong et al., 2020 (23)	×			×	×		×	×			-	×					
	Wang et al., 2021 (24)	×			×		×	×	×				×					
	Nourinejad and Ramezani, 2020 (25)				×	×		×						×				
	Zhang and Nie, 2021 (10)				×	×		×				×		×	×			
	Liang et al., 2023 (11)	×			×			×	×			×		×	*×			
	Narayan et al., 2019 (12)	×			×	×		×	X			×		×				
	Wei et al., 2020 (13)				×	×		×	×			×	*x					
**	Fayed et al., 2023 (14)				×	×	×	×	×		×			×	×			
	Tang et al., 2021 (15)		×		×		×	×	×			×			*x			
	Ye et al., 2021 (16)			×	×				×			×				×		
	Zheng et al., 2020 (17)			×	×	×		×	×			×				×		
** * * * * * * * * * * * * * * * * * *	Liu and Geroliminis, 2017 (18)	×			×	×		×	×			×				×		
** * * * * * * * * * * * * * * * * * *	Fan et al., 2014 (19)			×	×	×	×	×	×			×				×		
**	Wang et al., 2022 (20)				×	×	×	×			×			×			×	
**	Geurs et al., $2016(21)$				×	×		×		×	×	×				×	×	
**	Du et al., 2022 (I)			×	×			×	×		×	×	×	×		×		×
**	Pi et al., $2019(4)$	×			×	×		×	×		×	×	*x	×		×		×
*	Ke et al., 2021 (22)				×	×		×	×			×		×			×	×
x x x x x x x x x x x x x x x x x x x	Zhu et al., 2020 (5)	×			×	×		×				×		×	*x			×
	This study	×	X		x	X	X	×			x	×	×	X	x	x	X	×

TABLE 2: List of notations.

Network S	Structure
E	Set of nodes.
O	Set of origin nodes.
D	Set of destination nodes.
ΤR	Set of transfer nodes.
N	Set of networks; $N = \{Road(RN), Metro(MN), Bike(BN), Walk(WN)\}.$
\mathbf{A}_n	Set of links in network <i>n</i> .
4 Ұ	Set of links: $A = \bigcup_{n \in \mathbb{N}} A_n$.
Y	Set of all travel modes; $\Psi = \{ \text{ car, bus, M, CP, CD, EH, RS, W, B, } I_{m1,m2} \}$ where $I_{m1,m2}$ is a combination of mode $m1$ and $m2$.
V	Set of fleet vehicles for ridesharing and e-hailing services.
D M ij	Set of paths for origin-destination (OD) pair (i, j) with mode m .
o _a	Binary coefficient equals to 1 if link a is an origin link; 0 Otherwise.
d_a	Binary coefficient equals to 1 if link a is a destination link; 0 Otherwise.
$\delta_{a,p,m}^{(i,j)}$	Binary coefficient equals to 1 if path p of mode m traverse link a between OD pair (i, j) ; 0 Otherwise.
$q^{(i,j)}$	Travel demand for OD pair (i, j) .
l	Travel definate for OD pair (i, j).
<u>Indices</u>	
j, j, r, s	Index of node, $i, j, r, s \in E$.
ı	Index of link (edge), $a \in A$.
m 	Index of mode, $m \in \Psi$.
p n	Index of path, $p \in P_{ij}^m$. Index of network, $n \in N$.
n	index of network, $n \in \mathbb{N}$.
Input Par	rameters - [Value for the experiments]
$\overline{L_a}$	Length of link a (Km).
Sp_n	Mean speed in network n (Km/h) - [M: 60, B: 10, W: 3].
$freq_{m,a}$	Frequency of travel mode m on link a (units/h) - [Bus: 3, M: 6].
R_m	Meeting rate of travel mode m (service/h) - [CP: {Toy network: 100, Sioux Falls: 500}, RS: {Toy
a	network: 200, Sioux Falls: 1000}, EH: {Toy network: 100, Sioux Falls: 1000}].
S_m	Average perking time for mode m (h) - [Bus: 0.04, M: 0.02, CP: 0.04, RS: 0.05, EH: 0.03].
P_m $TF_{m,a}$	Average parking time for mode m (h) - [car: 0.17, B: 0.08]. Trip fare of travel mode m on link a (\$) - [Bus: 0.3, M: 0.3, CP: 0.7, CD: 0.7, RS: 0.9, EH: 1.1].
PF_m	Parking fare for travel mode m (\$) - [car: 1].
CAP_m	Maximum passenger capacity for the travel mode m - [CP: 1, RS: 2].
Pk_cap_s	Parking capacity for transfer node s - [Toy network: 100, Sioux Falls: 800].
V	Fleet size for the ridesharing and e-hailing services - [Toy network: 1000, Sioux Falls: 3500].
α	Monetary cost per unit of time (\$/h) - [Toy network: 5, Sioux Falls: 20].
β	Monetary cost per unit of distance (\$/Km) - [0.25].
Variables	
$t_{a,n}$	Travel time on link a belonging to network n .
$WT_{m,a}$	Waiting time for travel mode m on link a .
$ST_{m,a}$	Service time for travel mode <i>m</i> on link <i>a</i> .
$C_{m,a}$	Monetary cost of using travel mode m on link a .
x_a	Aggregated traffic flow on link a.
$x_{a,m}$	Aggregated traffic flow on link a with travel mode m .
q_m	Travel demand for mode m .
$q_m^{(i,j)}$	Travel demand for mode m and OD pair (i, j) .
$a^{(i,j)}$	Number of empty or occupied service vehicles between OD pair (i, j) ; $t \in \{e, o\}$.
$q_o^{(i,j)}$ r	Number of occupied service vehicles between OD pair (i, j) stopping at node r .
$c^{(i,j)}$	Generalized cost of path p with travel mode m between OD pair (i, j) .
$f^{(i,j)}$	
$f_{p,m}^{(i,j)}$ $f_{p,m}^{(i,j)r,s}$	Traffic flow of mode m on path p between OD pair (i, j) .
$f_{p,m}^{(i,j)}$ $f_{p,m}^{(i,j)r,s}$ $f_{p,CD}^{(i,j)}$	Traffic flow of carpooling drivers on path p between (i, j) stopping at nodes r and s .
$q_{0}^{(i,j)} r$ $q_{0}^{(i,j)} r$ $c_{p,m}$ $f_{p,m}^{(i,j)}$ $f_{p,cD}^{(i,j)}$ $f_{p,cD}^{(i,j)}$ $y_{p,t}^{(i,j)}$ $y_{p,RS}^{(i,j)}$	

1 cle. Additionally, they can go to their destination by walking (W) or biking (B). Accordingly, we 2 define Ψ as the set of travel modes ($\Psi = \{car, bus, M, W, B, CD, CP, EH, RS\}$).

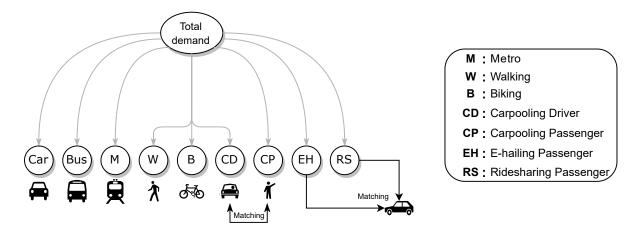


FIGURE 1: Available travel options for multi-modal networks, without intermodality.

To consider interactions between the modes in terms of congestion effects, we represent the physical network by four subnetworks: road (RN), walking (WN), biking (BN), and metro (MN) network. Buses and cars both use the road network and contribute to traffic congestion. N denotes the set of networks, $N = \{RN, WN, BN, MN\} \forall RN, WN, BN, MN \subset A$. The model is formulated for a given time period to represent the state of the network, following two well-known principles: UE and SO. Thus, the model is presented in a time-independent context, which keeps it tractable

10 UE and SO Objective Function

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and analytically solvable.

- 11 This subsection presents the objective functions of UE and SO and how each component of these
- 12 functions is calculated. In particular, we present the cost functions for commuters at the link level
- 13 for all the modes mentioned in Figure 1.

The generalized cost is the normalized sum of travel, waiting, service, and monetary costs (4). Every one of these terms is defined separately for each mode. This leads to a piece-wise objective function and, thus, a non-convex MIQP program. To assign traffic based on the UE principle and calculate the equilibrium through Beckmann transformation (26), we define the objective function as follows:

$$\min Z_{UE} = \sum_{n \in \mathbb{N}} \sum_{a \in A_n} \int_0^{x_a} \alpha \cdot t_{a,n}(\omega) d\omega + \sum_{a \in A} \sum_{m \in \Psi} [\alpha(WT_{m,a} + ST_{m,a}) + C_{m,a}] \cdot x_{a,m}$$
(1)

where, α denotes the value of time (27), $x_{a,m}$ is the flow of mode m on link a and x_a denotes the total flow of link a. $t_{a,n}$ denotes the travel time on the link a (i.e., the in-vehicle time), which is calculated by Equation (2) based on the network to which the link belongs. For the road network (RN), the link travel time increases with the flow. In this study, we use the well-known Bureau of Public Roads (BPR) function (26). For the other networks, the link travel time depends on the link length (L_a) and the average speed (Sp_n) of walking, biking, and metro, respectively.

$$t_{a,n}(x) = \begin{cases} BPR(x) & if \ n = RN \\ \frac{L_a}{Sp_n} & if \ n \in \{MN, WN, BN\} \end{cases}$$
 (2)

Equation (3) defines $WT_{m,a}$ as the waiting time of mode m on link a. A commuter has a waiting time at the start of the trip, so it is only counted for links attached to an origin node (ensured by o_a). For PT, the waiting time is assumed to be half of the headway (inspired by (4) and (20)). For SMSs, based on (25), we assume that the waiting time depends on the number of passengers in the system (q_m) and the meeting rate (R_m) . R_m expresses the rate of pickups in the network and can be estimated by the cobb-douglas function (13). Here, we set an average constant rate that should be estimated from real-world SMSs data.

$$WT_{m,a} = \begin{cases} 0 & if \ m \in \{car, CD, W, B\} \\ \frac{1}{2freq_{m,a}} \cdot o_a & if \ m \in \{Bus, M\} \\ \frac{q_m}{R_m} \cdot o_a & if \ m \in \{CP, RS, EH\} \end{cases}$$

$$(3)$$

 $ST_{m,a}$ in Equation (4) is the service time of mode m on link a. For PT, it denotes the average time spent at each stop (S_{Bus} , S_M for bus and metro). For car or bike users, it represents the parking time (P_{car} and P_B) and is only counted for destination links (represented by d_a). $ST_{m,a}$ for SMSs represent the time to be matched with a driver/passenger and the boarding and drop-off times (S_m ; $m \in \{CP, RS, EH\}$) on origin and destination links. Additionally, a CD experiences parking time at his destination. Walking does not have a service time.

$$ST_{m,a} = \begin{cases} 0 & if \ m = W \\ S_m & if \ m \in \{Bus, M\} \\ S_m \cdot (o_a + d_a) & if \ m \in \{CP, RS, EH\} \\ S_m \cdot (o_a + d_a) + P_1 \cdot d_a & if \ m = CD \\ P_m \cdot d_a & if \ m \in \{car, B\} \end{cases}$$
(4)

Equation (5) denotes the monetary cost of mode m on link a. Based on (l), for solo drivers, it includes the cost of using the car (i.e., fuel cost) for the traveled distance and the parking fare (PF_{car}) at the destination. For all other passengers (PT and SMSs passengers), $C_{m,a}$ represents the trip fare to be paid ($TF_{m,a}$). For carpooling drivers, the trip fare received from passengers is retrieved from the cost of using their car. For walking and biking, we assume no monetary cost.

$$C_{m,a} = \begin{cases} \gamma \cdot L_a + PF_m \cdot d_a & if \ m = car \\ TF_{m,a} & if \ m \in \{Bus, M, CP, EH, RS\} \\ \gamma \cdot L_a + PF_m \cdot d_a - TF_{m,a} & if \ m = CD \\ 0 & if \ m \in \{W, B\} \end{cases}$$

$$(5)$$

14 Using these same definitions, we define the SO objective function as:

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$$\min Z_{SO} = \sum_{n \in \mathbb{N}} \sum_{a \in A_n} \alpha \cdot t_{a,n}(x_a) \cdot x_a + \sum_{a \in A} \sum_{m \in \Psi} [\alpha(WT_{m,a} + ST_{m,a}) + C_{m,a}] \cdot x_{a,m}$$
 (6)

1 This objective function, Z_{SO} , minimizes the system's total cost. Before introducing intermodality, we present the model's constraints for a multi-modal network without intermodality.

- Model's Linear Constraints for Mode and Path Choice
- The objective functions previously described are formulated in terms of link flow and cost. How-
- ever, commuters are confronted with mode and path choices. Thus, let $f_{p,m}^{(i,j)}$ be the path flow
- variable. Equation (7) presents the link-path flow conversion, and Equation (8) represents the
- demand conservation constraint.

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$$x_{a,m} = \sum_{i,j \in E} \sum_{p \in P_{ii}^m} f_{p,m}^{(i,j)} \cdot \delta_{a,p,m}^{(i,j)} \qquad \forall a \in A \quad ; \forall m \in \Psi$$
 (7)

$$q^{(i,j)} = \sum_{m \in \Psi} \sum_{p \in P_{ij}^m} f_{p,m}^{(i,j)} \qquad \forall i, j \in E$$

$$(8)$$

9 Here, we present the construction for every considered mobility option. Equations (9)-(11) are

for the carpooling service. Based on (1), we define $f_{p,CD}^{(i,j)\,r,s}$ as the number of carpooling drivers

traveling between (i, j), with path p and stopping at nodes r and s to pick up or drop off their 11

passengers. Note that a CD can have more than one passenger onboard. Thus, $f_{p,CD}^{(i,j)\ i,j}$ expresses 12

the number of CD having passengers with the same OD pair (i, j). Constraint (9) ensures that the 13

total number of CD between (i, j) is the sum of the drivers stopping at the different passengers'

OD pairs on path p. To formulate the correspondence between the drivers' and passengers' paths, 15

let us define the following sets: 16

• $Q_p^{(r,s)}$: Set of paths l between (r,s), where the path p is a sub-path of l. • $R_p^{(r,s)}$: Set of paths l (r,s), where l is a sub-path of p.

Constraint (10) ensures that drivers can pick up all carpooling passengers. Recall that the drivers can have the same OD pair as the passengers or not. Figure 2 illustrates the correspondence between the carpooling passenger and driver paths, expressed by these constraints. Constraint (11) ensures that all CD stopping at nodes r and s have enough passengers between (r,s). We formulated these constraints regarding path flow variables to ensure the passenger-driver conservation over the path p.

$$f_{p,CD}^{(i,j)} = \sum_{r \in F} f_{p,CD}^{(i,j)r} \qquad \forall i, j \in E \quad ; \forall p \in P_{ij}^{CD}$$
 (9)

$$f_{p,CP}^{(i,j)} \le CAP_{CP} \cdot \left[\sum_{r,s \in E} \sum_{l \in \mathcal{Q}_p^{(r,s)}} f_{l,CD}^{(r,s)i,j} \right] \qquad \forall i, j \in E \quad ; \forall p \in P_{ij}^{CP}$$
 (10)

$$f_{l,CD}^{(i,j)\,r,s} \le f_{p,CP}^{(r,s)} \qquad \qquad \forall r,s,i,j \in E \quad ; \forall l \in P_{ij}^{CD} \quad ; \forall p \in R_l^{(r,s)} \qquad \qquad (11)$$

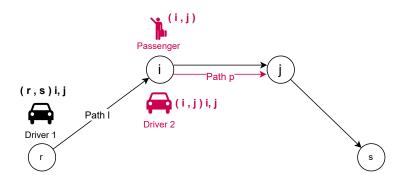


FIGURE 2: Correspondence between the carpooling passenger's and drivers' path.

For the e-hailing, $y_{p,EH}^{(i,j)}$ denotes the number of fleet vehicles having an e-hailing passenger between (i,j) with path p. Constraint (12) ensures that this variable equals the corresponding e-hailing path flow variable.

$$f_{p,EH}^{(i,j)} = y_{p,EH}^{(i,j)} \qquad \forall i, j \in E \quad ; \forall p \in P_{ij}^{EH}$$
 (12)

Inspired by the formulation of carpooling in (1) and (4), we propose a ride-sharing service formulation. Let $y_{p,RS}^{i,r,s,j}$ represents the number of fleet vehicles participating in a ridesharing service and stopping at nodes i, j, r and s to pick up or drop off passengers. The ordering of the nodes in this variable is whether a First In First Out (FIFO) or Last In First Out (LIFO) service, as illustrated in Figure 3.

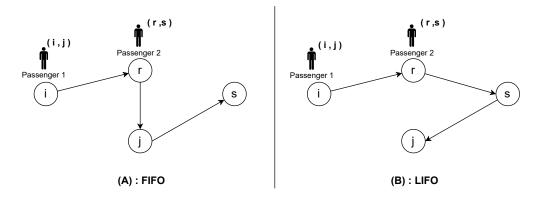


FIGURE 3: Order of ridesharing service. (A): The first picked-up passenger is the first dropped-off; (B): The first picked-up passenger is the last dropped-off.

Equation (13) defines the number of ridesharing vehicles traveling between (i, j) with path p. Similar to the carpooling service, Constraint (14) ensures enough seats for the passengers, and Constraint (15) ensures enough passengers for the ridesharing cars. CAP_{RS} denotes the ridesharing passenger capacity, which is the same for all RS vehicles.

$$y_{p,RS}^{(i,j)} = \sum_{r,s \in E} y_{p,RS}^{i,r,s,j} \qquad \forall i, j \in E \quad ; \forall p \in P_{ij}^{RS}$$
 (13)

$$f_{p,RS}^{(i,j)} \le CAP_{RS} \cdot \left[\sum_{r,s \in E} \sum_{l \in O_p^{(r,s)}} (y_{l,RS}^{r,i,j,s} + y_{l,RS}^{r,i,s,j}) \right] \qquad \forall i, j \in E \quad ; \forall p \in P_{ij}^{RS}$$
 (14)

$$y_{l,RS}^{i,r,s,j} + y_{l,RS}^{i,r,j,s} \le f_{p,RS}^{(r,s)} \qquad \forall r, s, i, j \in E \quad ; \forall l \in P_{ij}^{RS} \quad ; \forall p \in R_p^{(r,s)}$$

$$(15)$$

Constraint (16) ensures that the ridesharing passengers are sharing the trip with another passenger (not an e-hailing service). Note that $y_{p,RS}^{i,i,j,j}$ represents the ridesharing vehicles on path p having passengers with the same OD pair (i,j). This is different from carpooling, as the driver providing the service is not a commuter himself.

$$f_{p,RS}^{(i,j)} \ge 2 \cdot y_{p,RS}^{i,i,j,j} + \sum_{r,s \in E} \sum_{l \in O_n^{(r,s)}} (y_{l,RS}^{r,i,j,s} + y_{l,RS}^{r,i,s,j}) \qquad \forall i, j \in E \quad ; \forall p \in P_{ij}^{RS}$$
(16)

6 Constraints (17) and (18) define the number of occupied fleet cars as the sum of cars participating 7 in the e-hailing and ridesharing services.

$$q_o^{(i,j) r} = \sum_{p \in P_{ij}^{RS}} y_{p,RS}^{i,r,s,j} + y_{p,RS}^{i,s,r,j}$$
 $\forall i, j, r \in E$ (17)

$$q_o^{(i,j)} = \sum_{r \in E} q_o^{(i,j)} + \sum_{p \in P_{ij}^{EH}} y_{p,EH}^{(i,j)}$$
 $\forall i, j \in E$ (18)

Based on the formulation of the SMSs, we need to conserve the passengers and drivers flow over the paths. $y_{p,e}^{(i,j)}$ denotes the number of empty fleet vehicles traveling between (i,j) with path p. Constraint (20) ensures, for every destination node, the number of entering vehicles equals the number of exiting vehicles. Constraint (21) ensures, for every origin node, there are enough empty cars to pick up the e-hailing and ridesharing passengers. Constraint (22) ensures the fleet size (|V|)conservation. Constraints (23)-(25) are integrality conditions on the decision variables.

$$q_e^{(i,j)} = \sum_{p \in P_{ii}^{EH}} y_{p,e}^{(i,j)}$$
 $\forall i, j \in E$ (19)

$$\sum_{i,j \in E} q_o^{(i,j) s} + \sum_{j \in E} q_e^{(j,s)} = \sum_{j \in E} q_o^{(s,j)} + \sum_{j \in E} q_e^{(s,j)}$$
 $\forall s \in D$ (20)

$$\sum_{i \in E} q_o^{(i,j)} \ge \sum_{s \in E} q_o^{(j,s)} \tag{21}$$

$$\sum_{i,j\in E} q_o^{(i,j)} + q_e^{(i,j)} = |V| \tag{22}$$

$$f_{p,m}^{(i,j)}, f_{p,CD}^{(i,j)r,s} \ge 0 \qquad \forall p \in P_{ij}^m \quad ; \forall i, j, r, s \in E \quad ; \forall m \in \Psi \quad (23)$$

$$y_{p,m}^{(i,j)} \ge 0 \qquad \forall p \in P_{ij}^m \quad ; \forall i, j \in E \quad ; \forall m \in \{EH, RS, e\} \quad (24)$$

$$y_{p,RS}^{i,r,s,j} \ge 0$$
 $\forall p \in P_{ij}^{RS} \quad ; \forall i,j,r,s \in E \quad (25)$

Link Flow and Path Flow Correspondence

The UE and SO objective functions, formulated in section 4.1.1, require the calculation of x_a and $x_{a,m}$. Following Beckmann's formulation, $x_{a,m}$ is defined by Equation (7). However, to calculate the x_a variable used in links travel time, we consider the travel modes that contribute to traffic congestion, occupied and empty fleet vehicles, and PT flow. Considering PT flow means that we need to count PT units independently of the passenger flow. This is consistent with reality since PT adheres to a well-defined schedule and operates even with no passengers. It is worth mentioning that multiple studies (e.g., (7), (1) and (28)) formulate only non-empty PT for links, which is not the case in our study. To do so, we use the frequency of PT on every link to count the units, as 10 described by Equation (26).

$$x_{a} = \sum_{m \in \Psi'} x_{a,m} + \sum_{l \in PT} freq_{l,a} + \sum_{i,j \in E} \sum_{p \in P_{ij}^{RS}} y_{p,RS}^{(i,j)} \cdot \delta_{a,p,RS}^{(i,j)} + \sum_{i,j \in E} \sum_{p \in P_{ij}^{EH}} (y_{p,EH}^{(i,j)} + y_{p,e}^{(i,j)}) \cdot \delta_{a,p,EH}^{(i,j)}$$
(26)

 $\forall a \in A \quad ; \Psi' = \{car, CD, W, B\} \quad ; PT = \{bus, M\}$

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Regarding the carpooling service, we only count the driver flow. For the ridesharing service, we are 12 adding the number of cars instead of the passenger flow since a vehicle may carry multiple passengers. With this, we keep the link and path flows as the number of vehicles. At this point, all modes are defined, and their travel cost functions are formulated. Now we can introduce intermodality. 15

Multi-Modal Transportation Network with Intermodality 16

17 This section introduces the transformation of the model's constraints and variables to consider intermodality. In this study, an inter-mode is any combination of the previously enumerated modes 18 (Figure 1) and is considered as a separate mode. For example, Park-and-Ride as a travel option is the commuter who uses his car to a transfer node and then takes the metro (3). 20

The proposed model can consider any logical combination of modes as a travel option without further modifications. However, we are mainly interested in inter-modes, including PT and SMSs. We will focus on intermodality, as represented in Figure 4. Thus, the set of modes Ψ is extended to include all modes in the form of $I_{m1,m2}$ where m1 and $m2 \in \Psi$.

As we are considering every inter-mode as a separate mode, commuters between (i, j) with an inter-mode $m = I_{m1,m2}$ on path p ($p = p1 \oplus p2$, where \oplus is the concatenation of two paths), use mode m1 with path p1, up to a transfer node. Then, they use m2 with path p2 to their destination. The number of commuters between (i, j) with an inter-mode m using path p is represented by the path flow variable $f_{p,m}^{(i,j)}$. Note that the model can consider a combination of more than two modes $I_{m1,m2}$, where m1 is a 'simple' mode and m2 is an inter-mode (and vice-versa).

Let PI((i, j), s) be the set of all inter-modal paths between (i, j) in which the node s is the transfer node. Constraint (27) ensures the number of commuters using their car as part of an inter-mode and transferring at node s does not exceed the parking capacity at node s, represented by Pk_cap_s .

$$\sum_{i,j \in E} \sum_{p \in PI((i,j),s)} f_{p,I_{car,M}}^{(i,j)} + f_{p,I_{CD,M}}^{(i,j)} \le Pk_cap_s \qquad \forall s \in TR$$
 (27)

To clearly represent intermodality, let I(m) denotes an inter-mode including the simple mode m

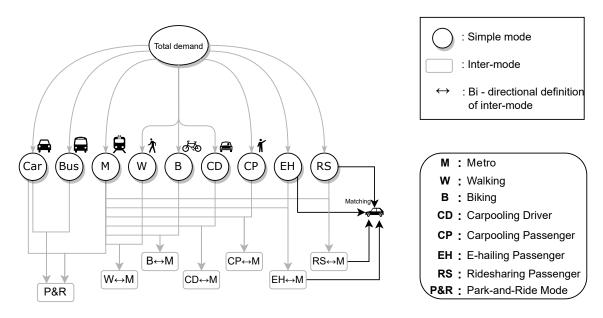


FIGURE 4: Available travel options for multi-modal networks, with intermodality.

(either as the first part or the second part of the inter-mode). m(p) denotes the part of path p where the mode m is used, and TR(p) denotes the transfer node of the inter-modal path p. To consider intermodality with carpooling, we add Constraints (28) and (29) to the model. Constraint (28) ensures that drivers can pick up the passengers participating in carpooling as part of an inter-mode. The right-hand side of the constraint considers drivers participating in carpooling as part of an inter-modal trip, as well as carpooling drivers between any OD pair (u, v) passing by the transfer node t of the passengers. This is illustrated by Figure 5. In other words, a passenger can be picked up by a driver going from his origin to his destination or by a driver going from his origin to the transfer node t.

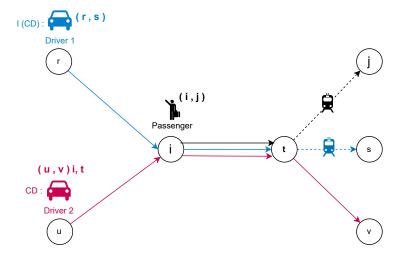


FIGURE 5: Correspondence between a carpooling passenger and drivers paths with intermodality.

$$f_{p,I(CP)}^{(i,j)} \leq CAP_{CP} \cdot (\sum_{I(CD) \in \Psi} \sum_{r,s \in E} \sum_{k \in \{x \in P_{rs}^{I(CD)} ; CP(x) = CP(p)\}} f_{k,I(CD)}^{(r,s)} + \sum_{u,v \in E} \sum_{l \in P_{uv}^{CD}} f_{l,CD}^{(u,v)i,t} + f_{l,CD}^{(u,v)t,j})$$

$$\forall i, j \in E \quad ; \forall p \in P_{ij}^{I(CP)} \quad ; t = TR(p)$$

$$(28)$$

Constraint (29) ensures all carpooling drivers between (i, j) have enough carpooling passengers to pick. This means that no CD is driving without a passenger on board, either for the full trip (i.e., same OD pair as passenger), or a part of the trip.

$$f_{p,I(CD)}^{(i,j)} \leq \sum_{I(CP) \in \Psi} \sum_{r,s \in E} \sum_{p' \in \{x \in P_{cs}^{I(CP)} \; ; \; CP(x) = CP(p)\}} f_{p',I(CP)}^{(r,s)} + \sum_{u,v \in E} \sum_{k \in \{x \in P_{uv}^{CP} \; ; \; x = CP(p)\}} f_{k,CP}^{(u,v)} \quad \forall i,j \in E \quad ; \; \forall p \in P_{ij}^{I(CD)} \quad (29)$$

4 Thus, we need to reformulate Constraints (10) and (11) to include intermodality.

$$f_{p,CP}^{(i,j)} \leq CAP_{CP} \cdot (\sum_{r,s \in E} \sum_{k \in Q_p^{(r,s)}} f_{k,CD}^{(r,s)} i,j + \sum_{I(CD) \in \Psi} \sum_{u,v \in E} \sum_{k \in \{x \in P_{uv}^{I(CD)} : CP(x) = p\}} f_{k,I(CD)}^{(u,v)}) \quad \forall i,j \in E \quad ; \forall p \in P_{ij}^{CP}$$

$$(30)$$

$$f_{p,CD}^{(i,j)\,r,s} \leq f_{k,CP}^{(r,s)} + \sum_{I(CP) \in \Psi} \sum_{u,v \in E} \sum_{k \in \{x \in P_{uv}^{I(CP)}\,;\, CP(x) = p\}} f_{k,I(CP)}^{(u,v)}) \quad \forall r,s,i,j \in E \quad ;\, \forall p \in P_{ij}^{CD} \quad ;\, \forall k \in R_p^{(r,s)}$$

- 5 Similarly, for e-hailing and ridesharing, Constraint (32) is added to the model, and Constraints (12)
- 6 and (15) are updated accordingly.

$$f_{p,I(RS)}^{(i,j)} \leq CAP_{RS} \cdot \sum_{r,s \in E} \sum_{k \in O_{r}^{(r,s)}} (y_{k,RS}^{r,i,TR(p),s} + y_{k,RS}^{r,i,s,TR(p)} + y_{k,RS}^{r,TR(p),j,s} + y_{k,RS}^{r,TR(p),s,j}) \quad \forall i, j \in E \quad ; \forall p \in P_{ij}^{I(RS)}$$

$$(32)$$

$$f_{p,EH}^{(i,j)} + \sum_{I(EH) \in \Psi} \sum_{u,v \in E} \sum_{k \in \{x \in P_{uv}^{I(EH)} : EH(x) = p\}} f_{k,I(EH)}^{(u,v)} = y_{p,EH}^{(i,j)} \qquad \forall i, j \in E \quad ; \forall p \in P_{ij}^{EH}$$
 (33)

$$y_{p,RS}^{i,r,s,j} + y_{p,RS}^{i,r,j,s} \le f_{k,RS}^{(r,s)} + \sum_{I(RS) \in \Psi} \sum_{u,v \in E} \sum_{k \in \{x \in P_{uv}^{I(RS)} : RS(x) = p\}} f_{k,I(RS)}^{(u,v)} \quad \forall r,s,i,j \in E \quad ; \forall p \in P_{ij}^{RS} \quad ; \forall k \in R_p^{(r,s)}$$
(34)

7 To have the link-path flow correspondence, we update the $x_{a,m}$ variable as described by Equation 8 (35).

$$x_{a,m} = \sum_{i,j \in E} \sum_{p \in P_{ij}^{m}} f_{p,m}^{(i,j)} \cdot \delta_{a,p,m}^{(i,j)} + \sum_{I(m) \in \Psi} \sum_{u,v \in E} \sum_{k \in P_{uv}^{I(m)}} f_{k,I(m)}^{(u,v)} \cdot \delta_{a,m(k),m}^{(u,TR(k))} \qquad \forall a \in A \quad ; \forall m \in \Psi$$
 (35)

10 Thus, the final comprehensive multi-modal mathematical formulation of UE (UE-CMF) is:

$$\min Z_{UE} = \sum_{n \in \mathbb{N}} \sum_{a \in A_n} \int_0^{x_a} \alpha \cdot t_{a,n}(\omega) \ d\omega + \sum_{a \in A} \sum_{m \in \Psi} \left[\alpha (WT_{m,a} + ST_{m,a}) + C_{m,a} \right] \cdot x_{a,m}$$
 (UE-CMF)

S.I.

(Cost functions
$$x_{a,m} = \sum_{i,j \in E} \sum_{p \in P_{ij}^{m}} f_{p,m}^{(i,j)} \cdot \delta_{a,p,m}^{(i,j)} \qquad \forall a \in A; \forall m \in \Psi$$

$$q^{(i,j)} = \sum_{m \in E} f_{p,CD}^{(i,j)} \qquad \forall i,j \in E$$

$$f_{p,CD}^{(i,j)} = \sum_{r \in E} f_{p,CD}^{(i,j)} \qquad \forall i,j \in E; \forall p \in P_{ij}^{CD} \qquad (9)$$

$$y_{p,RS}^{(i,j)} = \sum_{r \in E} f_{p,CD}^{(i,j)} \qquad \forall i,j \in E; \forall p \in P_{ij}^{CD} \qquad (13)$$

$$f_{p,RS}^{(i,j)} \leq CAP_{RS} \cdot \left[\sum_{r,s \in E} \sum_{l \in Q_p^{(rs)}} (y_{l,RS}^{r,i,s,j} + y_{l,RS}^{r,i,s,j})\right] \qquad \forall i,j \in E; \forall p \in P_{ij}^{RS} \qquad (13)$$

$$f_{p,RS}^{(i,j)} \geq \sum_{r \in E} f_{p,RS}^{(i,j)} \qquad \forall i,j \in E; \forall p \in P_{ij}^{RS} \qquad (14)$$

$$y_{l,RS}^{l,r,s,j} + y_{l,R,i,s}^{l,r,i,s} \leq f_{p,RS}^{r,s} \qquad \forall r,s,i,j \in E; \forall l \in P_{ij}^{RS}; \forall p \in R_p^{(rs)} \qquad (15)$$

$$f_{p,RS}^{(i,j)} \geq \sum_{p,RS} + \sum_{r,s \in E} \sum_{l \in Q_p^{(rs)}} (y_{l,RS}^{r,i,s,s} + y_{l,RS}^{r,i,s,j}) \qquad \forall i,j \in E; \forall p \in P_{ij}^{RS} \qquad (16)$$

$$q_{o}^{(i,j)} = \sum_{p \in P_{ij}^{RS}} y_{p,RS}^{l,r,s,j} + y_{p,RS}^{l,s,r,j} \qquad \forall i,j \in E \qquad (17)$$

$$q_{o}^{(i,j)} = \sum_{p \in P_{ij}^{RS}} y_{p,e}^{(i,j)} + \sum_{p \in P_p^{HH}} y_{p,EH}^{(i,j)} \qquad \forall i,j \in E \qquad (18)$$

$$q_{e}^{(i,j)} = \sum_{p \in P_{ij}^{RS}} y_{p,e}^{(i,s)} \qquad \forall i,j \in E \qquad (19)$$

$$\sum_{i,j \in E} q_{o}^{(i,j)} + \sum_{p \in E} q_{o}^{(j,s)} = \sum_{p \in E} q_{o}^{(s,j)} + \sum_{p \in E} q_{o}^{(s,j)} \qquad \forall i,j,r,s \in E; \forall m \in \Psi \qquad (23)$$

$$\sum_{i,j \in E} q_{o}^{(i,j)} + q_{e}^{(i,j)} = |V| \qquad (22)$$

$$f_{p,m}^{(i,j)}, f_{p,m}^{(i,j)} \geq 0 \qquad \forall p \in P_{ij}^{RS}, \forall i,j,r,s \in E \qquad (24)$$

$$y_{p,RS}^{(i,j)} \geq 0 \qquad \forall p \in P_{ij}^{RS}, \forall i,j,r,s \in E \qquad (25)$$
Intermodality Constraints

- To address the SO principle, only the objective function in UE-CMF needs to be replaced by
- 2 Equation (6) and the problem can be treated as any minimization problem and solved by common
- (open-source or commercial) solvers. Our model's formulation allowed the use of these solvers
- for UE as well. In what follows, we provide the proof that the MIQP UE-CMF follows Beckmann
- transformation, and thus, the solutions satisfy UE conditions.
- **Proposition 1.** Solution of optimization problem UE-CMF satisfies user equilibrium conditions.

Proof. Following (26) and (24) procedures, let μ_{rs} $(r, s \in E)$ denote the dual variable 7 associated with the flow conservation constraint in Equation (8). Thus, the Lagrangian can be 8

$$L(f,\mu) = Z + \sum_{r,s \in E} \mu_{r,s} (q^{(r,s)} - \sum_{m \in \Psi} \sum_{p \in P_{rs}^m} f_{p,m}^{(r,s)})$$
(36)

10 We compute the derivatives of the Lagrangian, w.r.t the path flow and the dual variables, to express the KKT conditions. To simplify the equations, we assume in what is next that $\alpha = 1$. 11

Derivatives w.r.t path flow variable: 12

1. If $m \notin \{CP, RS, EH\}$: the terms WT, ST, and C in the objective function are constants 13 w.r.t the path flow. Thus, we obtain the following derivatives: 14

$$\frac{\partial Z}{\partial f_{p,m}^{(i,j)}} = \sum_{b \in A} \frac{\partial}{\partial x_b} \left\{ \sum_{n \in N} \sum_{a \in A_n} \int_0^{x_a} t_{a,n}(\omega) d\omega \right\} \times \frac{\partial x_b}{\partial f_{p,m}^{(i,j)}} + \sum_{b \in A} \sum_{m' \in \Psi} \frac{\partial}{\partial x_{b,m'}} \left\{ \sum_{a \in A} \sum_{m \in \Psi} [WT_{m,a} + ST_{m,a} + C_{m,a}] \cdot x_{a,m} \right\} \times \frac{\partial x_{b,m'}}{\partial f_{p,m}^{(i,j)}}$$
(37)

$$= \sum_{b \in A} t_{b,n}(x_b) \cdot \delta_{b,p,m}^{(i,j)} + \sum_{b \in A} [WT_{m,b} + ST_{m,b} + C_{m,b}] \times \delta_{b,p,m}^{(i,j)}$$
(38)

$$= \sum_{b \in A} \left[t_{b,n}(x_b) + W T_{m,b} + S T_{m,b} + C_{m,b} \right] \times \delta_{b,p,m}^{(i,j)}$$
(39)

$$=c_{p,m}^{(i,j)} \qquad \forall i,j \in E \quad ; \forall p \in P_{ij}^{m}$$

$$\tag{40}$$

2. If $m \in \{CP, RS, EH\}$: the terms ST and C in the objective function are constants w.r.t the path flow, while WT is not. Let us define G_b ($\forall b \in N$) as bellow:

$$G_{b,m} = \frac{\partial W T_{m,b}}{\partial x_{b,m}} \tag{41}$$

$$= \frac{\partial WT_{m,b}}{\partial f_{p,m}^{(i,j)}} \times \frac{\partial f_{p,m}^{(i,j)}}{\partial x_{b,m}}$$
(42)

$$=\frac{1}{R_m} \times \frac{1}{\delta_{b,n,m}^{(i,j)}} \tag{43}$$

The transition from Equation (41) to Equation (42) is by applying the chain rule of differentiation. The transition from Equation (42) to Equation (43) is explained by the fact that the waiting time for a passenger using an SMS depends only on the number of passengers using that same service. Also, the incidence matrix $[(\delta_{a,p,m}^{(i,j)})_{i,j\in E}]_{;a\in A}, m\in\Psi, p\in P_{ij}^m]$ is predefined and fixed for every network, and depends on neither the flow variables nor the OD demand. Then, as we are working with the same boundaries for functions f and f, we can use the property of derivatives, which states that: if $\frac{\partial x}{\partial f} = g$, then $\frac{\partial f}{\partial x} = \frac{1}{g}$. With this, we calculate the derivative of the objective function w.r.t the flow variable.

$$\frac{\partial Z}{\partial f_{p,m}^{(i,j)}} = \sum_{b \in A} \frac{\partial}{\partial x_b} \left\{ \sum_{n \in N} \sum_{a \in A_n} \int_0^{x_a} t_{a,n}(\omega) d\omega \right\} \times \frac{\partial x_b}{\partial f_{p,m}^{(i,j)}} + \sum_{b \in A} \sum_{m' \in \Psi} \frac{\partial}{\partial x_{b,m'}} \left\{ \sum_{a \in A} \sum_{m \in \Psi} [WT_{m,a} + ST_{m,a} + C_{m,a}] \cdot x_{a,m} \right\} \times \frac{\partial x_{b,m'}}{\partial f_{p,m}^{(i,j)}} \tag{44}$$

$$= \sum_{b \in A} t_{b,n}(x_b) \cdot \delta_{b,p,m}^{(i,j)} + \sum_{b \in A} [WT_{m,b} + ST_{m,b} + C_{m,b} + \frac{\partial WT_{m,b}}{\partial x_{b,m}} \cdot x_{b,m}] \times \delta_{b,p,m}^{(i,j)}$$
(45)

$$= \sum_{b \in A} \left[t_{b,n}(x_b) + W T_{m,b} + S T_{m,b} + C_{m,b} + G_{b,m} \cdot x_{b,m} \right] \times \delta_{b,p,m}^{(i,j)}$$
(46)

$$=c_{p,m}^{(i,j)} \qquad \forall i,j \in E \quad ; \forall p \in P_{ij}^{m}$$

$$\tag{47}$$

1 In conclusion, the derivative of the Lagrangian is calculated as follows:

$$\frac{\partial L(f,u)}{\partial f_{p,m}^{(i,j)}} = \frac{\partial Z}{\partial f_{p,m}^{(i,j)}} + \frac{\partial}{\partial f_{p,m}^{(i,j)}} \{ \sum_{r,s \in E} \mu_{r,s} (q^{(r,s)} - \sum_{m \in \Psi} \sum_{p \in P_{rs}^m} f_{p,m}^{(r,s)}) \}$$
(48)

$$=c_{p,m}^{(i,j)}-\mu_{ij} \qquad \forall i,j\in E \quad ; \forall m\in \Psi \quad ; \forall p\in P_{ij}^{m}$$

$$\tag{49}$$

- 2 Using these derivatives, we can explicitly formulate the minimization problem in UE-CMF with
- 3 the following UE conditions, which complete our proof.

$$f_{p,m}^{(i,j)}(c_{p,m}^{(i,j)} - \mu_{ij}) = 0 \qquad \forall i, j \in E \quad \forall m \in \Psi \quad \forall p \in P_{ij}^m$$

$$\tag{50}$$

$$c_{p,m}^{(i,j)} - \mu_{ij} \ge 0 \qquad \forall i, j \in E \quad \forall m \in \Psi \quad \forall p \in P_{ij}^{m}$$

$$(51)$$

$$\sum_{m \in \Psi} \sum_{p \in P_{ij}^m} f_{p,m}^{(i,j)} = q^{(i,j)} \qquad \forall i, j \in E$$

$$(52)$$

$$f_{p,m}^{(i,j)} \ge 0 \qquad \forall i, j \in E \quad \forall m \in \Psi \quad \forall p \in P_{ij}^{m}$$
 (53)

- 4 Since the objective function in program UE-CMF is non-convex, the uniqueness of equilibrium so-
- 5 lutions can be proven at the link level if all cost functions remain strictly monotone (29). However,
- 6 the uniqueness w.r.t path flows is not straightforward. In other words, there could exist an infinite
- 7 number of path flow solutions leading to the same unique link flow solution (30).

8 NUMERICAL RESULTS

- 9 In this section, we present the numerical results obtained from our study, which aims to analyze the
- 10 commuter's behavior under different scenarios. We first evaluate the proposed framework for a toy
- 11 network and perform an analysis to validate the model. Second, we apply the model for a larger
- multi-modal test case, the Sioux Falls network (31). By conducting this analysis, we also aim to
- 13 offer valuable insights into the decision-making process of commuters when selecting their mode

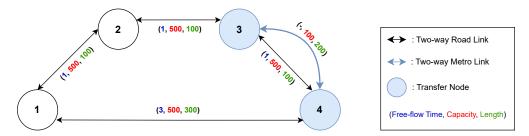


FIGURE 6: A multi-modal network with four nodes and twelve OD pairs.

- of transportation and the influential factors contributing to their choices. We solve the UE and SO
- 2 models using the Gurobi optimizer. Table 2 displays the experiment settings, with explicit mention
- 3 of differing values for the two test cases. Experiments were conducted on a 64-bit computer with
- 4 Intel i7 CPU 2.90GHz and 16GB RAM.

5 Validation and Analysis on a Toy Network

The proposed model is implemented for the network illustrated by Figure 6. The network has four nodes, serving as both origins and destinations. Nodes 3 and 4 are transfer nodes to the metro system. We assume a 100 commuter as demand for every OD pair.

We consider three scenarios, illustrated by Figure 7, and analyze the commuters' behavior under UE and SO principles. In Scenario (1), we only consider personal means of transport (car, walking, and biking) and PT (bus and metro). In Scenario (2), we allow SMSs as door-to-door services (without intermodality). Scenario (3) includes all possible travel options, i.e., SMSs and inter-modes are available. For this scenario, the model's solving time is 12 seconds.

Figure 8 presents the modes usage: the proportion of commuters using the travel mode. Additionally, Table 3 presents the traffic assignment regarding mode and path choices for the UE solution.

In Figure 8, Scenario (1), 66.67% of commuters choose PT. The bus mode is more used (with 50%) due to its accessibility. Since intermodality is not allowed, only commuters between OD pairs (3,4) and (4,3) can access the metro. This demonstrates that using PT when accessible is always preferable to personal means under both UE and SO principles. Let us take the bus service as an example. Bus units operate in the system independently of their passenger flow, contributing simultaneously to traffic congestion in the road network. Besides, a bus can hold more passengers than a simple car, and since we consider BPR as our travel time function, having as many commuters as possible going with PT is the best option. However, it is essential to acknowledge that PT has inherent limitations, like limited capacity and frequency, restricting its availability to all commuters. Consequently, some commuters will use private cars when PT is not viable. Consider the OD pair (2,3) as an example. This pair has no metro links between the origin and the destination. However, there are bus connections between Node 2 and Node 3. The commuters cannot use the bus mode because it has reached capacity due to hanging onboard passengers between OD pair (2,4).

Moreover, since the network is simple and uncongested, solutions under UE and SO are identical, following the observations in (32). None of the commuters in this scenario have opted for walking or biking due to the higher travel time associated with these modes than other options.

In Scenario (2), commuters can choose all modes without intermodality. Similar to the pre-

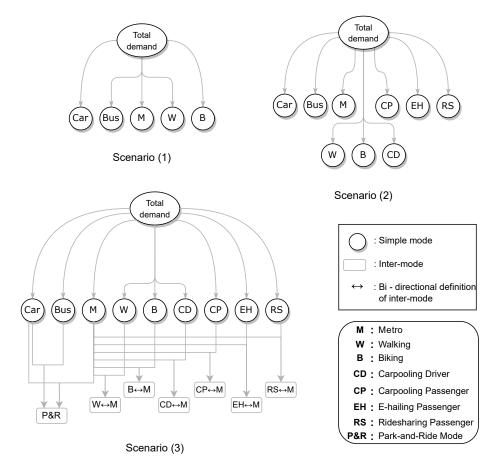


FIGURE 7: Available travel options for three scenarios.

vious scenario, bus mode is used to its full capacity. The metro is also preferred when accessible. For SMSs, 16.66% choose carpooling (both as passengers and drivers), and 16.67% used ridesharing. Table 3 shows that ridesharing is used for short-distance trips (OD pairs (2,3) and (3,2)) while carpooling is chosen for long-distance trips. This can be explained by the fact that ridesharing has a high trip fare, increasing with the length of the trip (traversed links). In this scenario, no commuter is willing to use his car or the e-hailing service because, without considering personal preferences, it is always beneficial to share the cost of the trip with a passenger through carpooling or ridesharing.

Note that under the UE conditions and for the same OD pair, the cost of carpooling passengers is not the same as that of drivers. For example, consider the OD pair (1,3). For these commuters, the bus is the option with minimum cost. Nevertheless, it reaches full capacity because of commuters between (1,2). The second best option is carpooling as a passenger. However, this can only be feasible if there are enough drivers, so only half of these commuters can choose CP mode. The cost for a carpooling driver is high due to the cost of using his car, but since this cost is less than driving alone or ridesharing, this option is used by the other half of commuters, described by Table 3.

When traffic is assigned under SO, the ridesharing service is not used. Our SO objective function does not consider the ridesharing service provider's profits. Thus, from a system point of

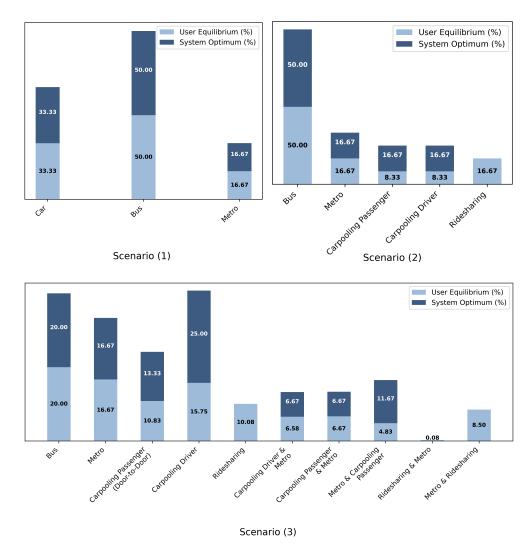


FIGURE 8: Modes usage in the small network, for three scenarios.

view, the goal is to reduce both the passengers' and drivers' costs. If the number of CP increases, the number of CD also increases accordingly, which will attract the demand to switch from the ridesharing service to the carpooling service.

In the third scenario, where the intermodality is available, we observed that, with the same model configuration as the two previous scenarios, more than 80% of commuters will use PT due to its accessibility, while the rest of the commuters will use carpooling. However, to present a more realistic and complete analysis, we reduce the bus frequency ($freq_{Bus} = 2$) and provide the traffic assignment information in Table 3. In this case, when traffic is assigned based on UE, 36.67% of commuters use PT, 10.83% carpool as passengers for door-to-door trips and not for intermodality, and 10.08% participate in ridesharing, while 15.75% of commuters use CD mode. These drivers benefit from the possibility of having a passenger on board (CP or I(CP)), for part or the entire trip to compensate for the high cost of using their car. Intermodality is used with SMSs, representing 26.66% of the trips (neither P&R mode nor walking and biking for the first/last mile). Similar to the previous scenario, ridesharing is mainly used for short trips (either as a door-to-door service or

TABLE 3: Traffic distribution for three scenarios.

OD pair	Mode	Path	Flow	Gen. Cost*	OD pair	Mode	Path	Flow	Gen. Cost*		
Scenario 1: Baseline Network											
(1,2)	Bus	1-2	100	6.487	(1,3)	car	1-2-3	100	64.158		
(1,4)	Bus	1-4	100	16.346	(2,1)	Bus	2-1	100	6.487		
(2,3)	car	2-3	100	32.154	(2,4)	Bus	2-3-4	100	12.975		
(3,1)	car	3-2-1	100	64.158	(3,2)	car	3-2	100	32.154		
(3,4)	M	3-4	100	17.483	(4,1)	Bus	4-1	100	16.346		
(4,2)	Bus	4-3-2	100	12.975	(4,3)	M	4-3	100	17.483		
Scenario 2: Multi-modal Network with SMSs											
(1,2)	Bus	1-2	100	1.522	(1,3)	CP	1-2-3	50	5.406		
(1,3)	CD	1-2-3	50	10.446	(1,4)	Bus	1-4	100	3.509		
(2,1)	Bus	2-1	100	1.522	(2,3)	RS	2-3	100	11.06		
(2,4)	Bus	2-3-4	100	3.045	(3,1)	CP	3-2-1	50	5.406		
(3,1)	CD	3-2-1	50	10.446	(3,2)	RS	3-2	100	11.060		
(3,4)	M	3-4	100	3.736	(4,1)	Bus	4-1	100	3.509		
(4,2)	Bus	4-3-2	100	3.045	(4,3)	M	4-3	100	3.736		
Scenario 3: Multi-modal Network with Intermodality (with $freq_{Bus} = 2$)											
$\overline{(1,2)}$	Bus	1-2	40	1.623	(1,2)	RS	1-2	60	11.063		
(1,3)	CP	1-2-3	80	7.342	(1,3)	CD	1-2-3	20	10.482		
(1,4)	Bus	1-4	40	3.591	(1,4)	CD&M	1-2-3-4	60	14.218		
(2,1)	Bus	2-1	40	1.629	(2,1)	RS	2-1	60	11.069		
(2,3)	Bus	2-3	40	1.638	(2,3)	CD	2-3	60	5.248		
(2,4)	CD&M	2-3-4	20	8.985	(2,4)	CP&M	2-3-4	80	7.415		
(3,1)	CD	3-2-1	100	10.494	(3,2)	Bus	3-2	40	1.644		
(3,2)	CP	3-2	30	3.684	(3,2)	CD	3-2	30	5.254		
(3,4)	M	3-4	100	3.736	(4,1)	Bus	4-1	40	3.591		
(4,1)	M&CP	4-1	60	11.090	(4,2)	M&RS	4-3-2	100	14.821		
(4,3)	M	4-3	100	3.736		1	h				

*: Generalized cost for using the corresponding mode and path between OD pairs.

combined with the metro for a short distance). In this case, ridesharing is used instead of carpooling due to the high demand for the carpooling service and, thus, a high waiting time. The trip with intermodality at the UE showed that our model could capture these complex trips. Recall that the model with inter-mode method can represent any trip, including multiple modes.

Under the SO principle, the ridesharing demand is directed toward carpooling. Here, many commuters use M&CP because increasing PT usage improves the system's overall objectives. This increase in the M&CP mode attracts more drivers to participate in carpooling (CD mode) to reduce their costs since they can transport passengers from the transfer node to their destination.

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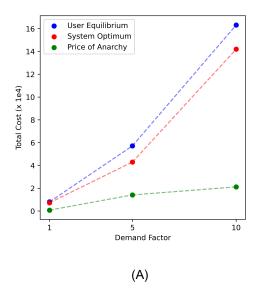
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We show in Figure 9(A) the total cost evolution under both UE and SO, when the total demand increases. The total cost under UE is approximately 1.2 times higher than SO when the demand is increased by a factor of 10. This means when the network is congested, commuters' personal decisions decrease the overall performance level of the transport system. It is expected due to the UE objective function. In such a case, increasing the capacity of PT, or promoting more carpooling through subsidies, for example, may help bring the solution under UE to that under SO.



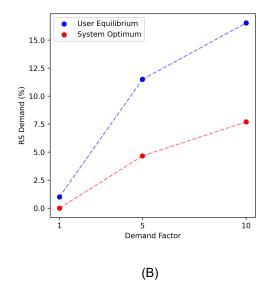


FIGURE 9: (**A**): Price of Anarchy - Evolution of the total cost in the small network; (**B**): Evolution of ridesharing usage for the small network, w.r.t the total demand.

Moreover, we investigate the variation in ridesharing usage when the total demand increases. Figure 9(B) illustrates, under UE, the use of ridesharing services increases which can be explained by the fact that, for carpooling drivers, ridesharing becomes more attractive since the travel time is high and the difference in terms of monetary cost between using their car and ridesharing becomes comparable. Besides, under SO, since the PT reaches its total capacity, demand is directed to carpooling and ridesharing. However, the ridesharing service is more present due to the high waiting time for carpooling passengers.

Application: Travel Behavior in Sioux Falls Network

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This section analyzes travel behavior in the multi-modal Sioux Falls network, with PT infrastructure extracted from (31) and illustrated by Figure 10. The network comprises 24 nodes, with nodes 4, 6, 15, and 19 as transfer nodes. We execute our model on 30 randomly selected OD pairs among 552 in total. The solving time is 61 seconds.

Figure 11 illustrates the proportion of commuters using each available mode. We can observe similar travel behavior as described in section 5.1. PT is widely used under both UE and SO principles. For UE, 26.65% of commuters choose intermodality with SMSs, which is higher than the SO mode choice distribution (16%). Similar to the previous case study, ridesharing is used for short-distance trips (OD pair (23,12) as door-to-door service, and (4,6), (6,4), (15,12), (19,12) combined with metro). For SO, the demand for the door-to-door ridesharing service and some of the metro and M&RS demand was directed towards the door-to-door carpooling service. As previously explained, reducing the carpooling drivers' cost (by satisfying more passengers) improve the system's objectives. In addition, 4.67% of commuters used the M&RS mode because of the high waiting time for the carpooling service, induced by the high number of passengers.

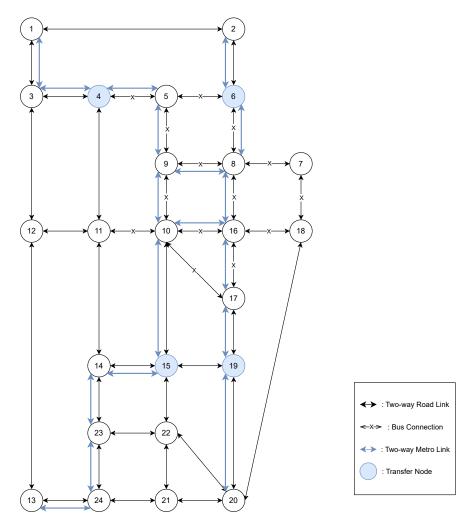


FIGURE 10: Sioux Falls Network with PT infrastructure.

CONCLUSION

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This research proposed a comprehensive mathematical assignment model for multi-modal urban transportation networks, including shared mobility services (SMSs) and public transport (PT). The model is able to address the impacts of SMSs on transportation systems and travelers' choices when integrated with PT. Existing studies have shown shortcomings in providing an integrated framework for evaluating, combining, and optimizing available travel options effectively, leading to potential inefficiencies in planning and higher expenses. In response, our proposed model, where commuters can seamlessly select and combine various travel modes, including SMSs and PT, allows for optimized travel choices.

Two fundamental assignment principles, user equilibrium (UE) and system optimum (SO), are considered for the model formulation (Program UE-CMF). The model not only includes transit, personal, and shared transportation modes but also captures the intermodality in which users can combine more than one travel mode. To the best of our knowledge, this is the most complete assignment model for the multi-modal network (refer to Table 1). We examined commuters' travel decisions under UE and SO. Our findings reveal carpooling is preferred over ridesharing when PT is not directly accessible. However, in situations of high demand and network congestion, rideshar-

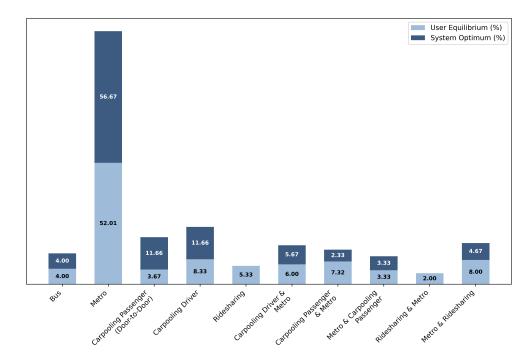


FIGURE 11: Modes usage in the multi-modal Sioux Falls network, with intermodality.

1 ing becomes more attractive due to increased waiting times for carpooling passengers and reduced costs between cars and ridesharing services. The proposed framework can provide valuable insights into travel behavior under different scenarios, contributing to a better understanding of the integrated transportation system.

As an initial step toward a unified framework incorporating SMSs and PT, our proposed model offers a baseline for analyzing commuters' behavior within a multi-modal transportation network. It facilitates the investigation of planning scenarios by providing insightful analyses of mode usage and traffic assignment in the network.

Future research should focus on integrating personal preferences and social criteria into 10 commuters' decision-making processes, incorporating service providers' objectives, and considering market equilibrium in the model's formulation. In addition, including traffic dynamics can enhance the model while increasing the system's complexity and solution calculation. The simulation-based approach can be applied while they make the system intractable for large-scale applications.

References 15

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- 16 1. Du, M., J. Zhou, A. Chen, and H. Tan, Modeling the capacity of multimodal and intermodal urban transportation networks that incorporate emerging travel modes. Transporta-17 tion Research Part E: Logistics and Transportation Review, Vol. 168, 2022, p. 102937. 18
- 19 Boarnet, M. G., G. Giuliano, Y. Hou, and E. J. Shin, First/last mile transit access as an 2. equity planning issue. Transportation Research Part A: Policy and Practice, Vol. 103, 20 2017, pp. 296-310. 21
- 22 3. Murphy, S. F. a. C., Transit Cooperative Research Program, Transportation Research

Board, and National Academies of Sciences, Engineering, and Medicine, *Shared Mobility*and the Transformation of Public Transit. Transportation Research Board, Washington,
D.C., 2016, pages: 23578.

- 4 4. Pi, X., W. Ma, and Z. S. Qian, A general formulation for multi-modal dynamic traffic assignment considering multi-class vehicles, public transit and parking. *Transportation Research Part C: Emerging Technologies*, Vol. 104, 2019, pp. 369–389.
- Zhu, Z., X. Qin, J. Ke, Z. Zheng, and H. Yang, Analysis of multi-modal commute behavior
 with feeding and competing ridesplitting services. *Transportation Research Part A: Policy* and Practice, Vol. 132, 2020, pp. 713–727.
- Wardrop, J., Some Theoretical Aspects of Road Traffic Research. *roceedings of the Institute of Civil Engineers, Part II*, 1952, pp. 325–378.
- 7. Di, X. and X. J. Ban, A unified equilibrium framework of new shared mobility systems. *Transportation Research Part B: Methodological*, Vol. 129, 2019, pp. 50–78.
- 8. Beojone, C. V. and N. Geroliminis, On the inefficiency of ride-sourcing services towards urban congestion. *Transportation Research Part C: Emerging Technologies*, Vol. 124, 2021, p. 102890.
- Yan, C.-Y., M.-B. Hu, R. Jiang, J. Long, J.-Y. Chen, and H.-X. Liu, Stochastic Ridesharing
 User Equilibrium in Transport Networks. *Networks and Spatial Economics*, Vol. 19, No. 4,
 2019, pp. 1007–1030.
- 20 10. Zhang, K. and Y. M. Nie, To pool or not to pool: Equilibrium, pricing and regulation. 21 *Transportation Research Part B: Methodological*, Vol. 151, 2021, pp. 59–90.
- Liang, Z., G. Jiang, and H. K. Lo, Dynamic equilibrium analyses in a ride-sourcing market under travel time uncertainty. *Transportation Research Part C: Emerging Technologies*, Vol. 153, 2023, p. 104222.
- Narayan, J., O. Cats, N. van Oort, and S. Hoogendoorn, Does ride-sourcing absorb the demand for car and public transport in Amsterdam? In 2019 6th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS), IEEE, Cracow, Poland, 2019, pp. 1–7.
- Wei, B., M. Saberi, F. Zhang, W. Liu, and S. T. Waller, Modeling and managing ridesharing in a multi-modal network with an aggregate traffic representation: A doubly dynamical approach. *Transportation Research Part C: Emerging Technologies*, Vol. 117, 2020, p. 102670.
- Fayed, L., G. Nilsson, and N. Geroliminis, On the utilization of dedicated bus lanes for pooled ride-hailing services. *Transportation Research Part B: Methodological*, Vol. 169, 2023, pp. 29–52.
- Tang, Z.-Y., L.-J. Tian, and D. Z. Wang, Multi-modal morning commute with endogenous shared autonomous vehicle penetration considering parking space constraint. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 151, 2021, p. 102354.
- Ye, J., Y. Jiang, J. Chen, Z. Liu, and R. Guo, Joint optimisation of transfer location and capacity for a capacitated multimodal transport network with elastic demand: a bi-level programming model and paradoxes. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 156, 2021, p. 102540.
- Zheng, Y., X. Zhang, and Z. Liang, Multimodal subsidy design for network capacity flex ibility optimization. *Transportation Research Part A: Policy and Practice*, Vol. 140, 2020,
 pp. 16–35.

1 18. Liu, W. and N. Geroliminis, Doubly dynamics for multi-modal networks with park-andride and adaptive pricing. *Transportation Research Part B: Methodological*, Vol. 102, 2017, pp. 162–179.

- Fan, W., M. B. Khan, J. Ma, and X. Jiang, Bilevel Programming Model for Locating Parkand-Ride Facilities. *Journal of Urban Planning and Development*, Vol. 140, No. 3, 2014, p. 04014007.
- Wang, Y., X. Lin, F. He, and M. Li, Designing transit-oriented multi-modal transportation
 systems considering travelers' choices. *Transportation Research Part B: Methodological*,
 Vol. 162, 2022, pp. 292–327.
- Geurs, K. T., L. La Paix, and S. Van Weperen, A multi-modal network approach to model public transport accessibility impacts of bicycle-train integration policies. *European Transport Research Review*, Vol. 8, No. 4, 2016, p. 25.
- 13 22. Ke, J., Z. Zhu, H. Yang, and Q. He, Equilibrium analyses and operational designs of 14 a coupled market with substitutive and complementary ride-sourcing services to public 15 transits. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 148, 16 2021, p. 102236.
- Zhong, L., K. Zhang, Y. (Marco) Nie, and J. Xu, Dynamic carpool in morning commute:
 Role of high-occupancy-vehicle (HOV) and high-occupancy-toll (HOT) lanes. *Transportation Research Part B: Methodological*, Vol. 135, 2020, pp. 98–119.
- 24. Wang, X., J. Wang, L. Guo, W. Liu, and X. Zhang, A convex programming approach
 for ridesharing user equilibrium under fixed driver/rider demand. *Transportation Research Part B: Methodological*, Vol. 149, 2021, pp. 33–51.
- Nourinejad, M. and M. Ramezani, Ride-Sourcing modeling and pricing in non-equilibrium two-sided markets. *Transportation Research Part B: Methodological*, Vol. 132, 2020, pp. 340–357.
- 26 26. Sheffi, Y., *Urban transportation networks: equilibrium analysis with mathematical programming methods.* Prentice-Hall, Englewood Cliffs, N.J, 1984.
- 28 27. Athira, I., C. Muneera, K. Krishnamurthy, and M. Anjaneyulu, Estimation of Value of 29 Travel Time for Work Trips. *Transportation Research Procedia*, Vol. 17, 2016, pp. 116– 30 123.
- Zhou, J., M. Du, and A. Chen, Multimodal Urban Transportation Network Capacity Model
 Considering Intermodal Transportation. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2676, No. 9, 2022, pp. 357–373.
- Ameli, M., J. P. Lebacque, and L. Leclercq, Evolution of multimodal final user equilibrium considering public transport network design history. *Transportmetrica B: Transport Dynamics*, Vol. 10, No. 1, 2022, pp. 923–953.
- 37 30. Rakha, H. and A. Tawfik, Traffic Networks: Dynamic Traffic Routing, Assignment, and Assessment. In *Encyclopedia of Complexity and Systems Science* (R. A. Meyers, ed.), Springer, New York, NY, 2009, pp. 9429–9470.
- 40 31. Yin, R., X. Liu, N. Zheng, and Z. Liu, Simulation-based analysis of second-best multi-41 modal network capacity. *Transportation Research Part C: Emerging Technologies*, Vol. 42 145, 2022, p. 103925.
- Prashker, J. N. and S. Bekhor, Some observations on stochastic user equilibrium and system optimum of traffic assignment. *Transportation Research Part B: Methodological*, Vol. 34, 2000, pp. 277–291.