# Macroscopic Modeling and Optimization of Two-Region Mixed Autonomy Network with Park-and-Ride

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# 1 INTRODUCTION

Connected and automated vehicles (CAVs) are generally expected to improve traffic safety and efficiency on future roads. Nevertheless, a consensus prevails that CAVs and human-driven vehicles (HDVs) are bound to coexist during a long transition period, leading to the so-called mixed autonomy networks. This coexistence will profoundly influence conventional urban traffic dynamics, with multimodal transportation incorporating park-and-ride (P&R) being one integral component. A novel dynamic macroscopic model of two-region (city center and periphery) mixed autonomy networks with P&R in the context of morning peak-hour commuting scenarios is proposed in this extended abstract. Such a model provides a quantitative tool to evaluate and optimize urban P&R policies and services. The contribution is twofold: (i) a two-region mixed autonomy network model with P&R is proposed which integrates an adaptive network macroscopic fundamental diagram (MFD) into the accumulation-based approach to effectively capture the mixed traffic dynamics; and (ii) P&R behavior, cruising-for-parking phenomenon, self-parking CAVs, and additional factors are modeled using an extended multi-pool representation of the system.

# 2 METHODOLOGY

## 2.1 Adaptive Macroscopic Fundamental Diagram

To account for the time-varying penetration rate of CAVs, the Markov chain method (Ghiasi et al., 2017; Zhou and Zhu, 2020) is applied to formulate the adaptive MFD considering the spatial distribution of CAVs across the region without forming platoons. Combined with the dual-regime traffic flow theory (Hou et al., 2013), the traffic condition is delineated into free-flow and congested regimes. A steady-state relationship between the space-mean speed, $V$, and accumulation, n, holds:

$$V = \begin{cases} V^{\text{free}}, & 0 \le n \le n_{\text{critical}}, \\ \dfrac{\frac{L}{n} - (s_0 + l_{\text{veh}})}{\sum_{k,k' \in \mathcal{K}} \mathbb{P}_k \mathbb{P}_{k'} h_{kk'}}, & n_{\text{critical}} \le n \le n_{\text{jam}}, \end{cases} \tag{1}$$

where $V^{\text{free}}$ is the free-flow speed, $L$ is the total network length, $s_0$ is the minimum gap between two adjacent vehicles, $l_{\text{veh}}$ is the average vehicle length, $\mathbb{P}_k$ and $\mathbb{P}_{k'}$ are respectively defined as the penetration rate of vehicles of type $k$ and $k'$, $k, k' \in \mathcal{K} = \{\text{cav}, \text{hdv}\}$, $h_{kk'}$ is the headway of each car-following type $kk'$, $n_{\text{critical}} = \frac{L}{V^{\text{free}} \sum_{k,k' \in \mathcal{K}} \mathbb{P}_k \mathbb{P}_{k'} h_{kk'} + s_0 + l_{\text{veh}}}$ represents the critical accumulation at which the speed start to decrease, and $n_{\text{jam}} = \frac{L}{s_0 + l_{\text{veh}}}$ represents the accumulation when the network is completely congested.

## 2.2 Cruising-for-Parking Distance Estimation

To estimate the cruising-for-parking distance, $l_{\text{cruise}}$, which is the key to calculating the cruising outflow, the piecewise functional form is employed (Gu et al., 2020; Belloche, 2015):

$$l_{\text{cruise}} = \begin{cases} d_p \cdot \dfrac{N_{\text{total}} + 1}{N_{\text{total}}(1 - O) + 1}, & 0 \leq O \leq O_{\text{critical}}, \\ a \exp[b \cdot O], & O_{\text{critical}} \leq O \leq 1, \end{cases} \tag{2}$$

where $d_p$ is the average distance between two adjacent parking spaces, $N_{\text{total}}$ is the total number of parking spots, $a$ and $b$ are parameters to be estimated, $O$ is the parking occupancy, and $O_{\text{critical}}$ is the parking occupancy of the first intersecting point of the two components. The first piece is derived using the idea of non-replacement sampling, while the second piece is an exponential function. Such a piecewise function can mitigate the underestimation of the former in the case of high parking occupancy, and the underestimation of the latter in the case of low parking occupancy.

## 2.3 Parking Choice Model

The utility function, integrating time and cost, underpins parking choice modeling for both HDVs and CAVs. HDVs confront a selection among three alternatives upon demand initiation: on-street parking in the city center, off-street parking in the city center, or utilizing P&R facilities situated at the boundary between the city center and the periphery. Factors such as driving costs, parking prices, metro fares, transit durations, etc., influence the decision-making process. To address the inherent uncertainty in driver decisions, the utility function incorporates random elements that adhere to an independent and identically distributed extreme value distribution. This setup facilitates the utilization of the multinomial logit (MNL) model to delineate the parking choice behavior of HDVs.

CAVs additionally consider parking at home or continuous driving after passenger drop-off. Due to post-destination decision-making nature of CAVs, time factors diminish compared to HDVs. As CAV choices are deterministic (assuming they are determined solely by algorithms), their utility lacks randomness. However, due to the inadequacy of the MNL model in capturing CAV decision-making dynamics and the oversimplification inherent in assuming that all CAVs within the region unilaterally opt for the alternative with the highest utility, a Monte Carlo simulation method may emerge as a suitable approach for elucidating CAV choice behaviors. This method involves sampling from specified distributions representing the variables associated with each CAV alternative and subsequently calculating the utilities for each alternative. The resulting ratio of instances where each option attains maximum utility to the total simulation count provides insights into the proportion of CAVs opting for each parking alternative.

## 2.4 System Dynamics Model

The urban network is divided into two regions, the city center ($c$) and the periphery ($p$). To model the two-region network considering both P&R, the multi-pool representation is utilized and extended in conjunction with the accumulation-based approach. The active vehicular accumulation in each region encompasses three families: (i) vehicles of family "moving" with demand for parking at public lots, (ii) vehicles of family "transit" necessitating parking at public lots, and (iii) vehicles of family "self" either self-parking to a specific alternative or continuing driving without parking. The city center additionally encompasses vehicles of family "cruise" cruising for on-street parking. One last family, "parked", which does not contribute to the active vehicular accumulation, comprises already parked vehicles.

Considering varying speeds of cruising-for-parking vehicles, $V^{\text{cruise}}$, compared to non-cruising ones, $V^{\text{noncru}}$, when the network is not severely congested and non-cruising vehicles, which consists of the first three mentioned vehicle families, can easily overtake cruising ones, the speed of non-cruising vehicles can be maintained and estimated by Eq. (1), i.e. $V^{\text{noncru}} = V$. The speed of cruising vehicles, however, will decrease from the maximum expected speed, $V^{\text{cruise,max}}$, to align with that of non-cruising vehicles under severely congested network. Therefore, $V^{\text{cruise}} = \min\{V^{\text{noncru}}, V^{\text{cruise,max}}\}$. Then, the outflow of specific composition $r$ of each family $x$ of vehicle type $k \in \{\text{cav}, \text{hdv}\}$ at simulation step $u$ can be estimated as follows:

$$o_{ij,k}^{x,r}(u) = \frac{n_{ij,k}^{x,r}(t_u)V_i^m}{l_{ij,k}^{x,r}} \cdot \Delta t \tag{3}$$

where $n_{ij,k}^{x,r}(t_u)$ and $l_{ij,k}^{x,r}$ are the corresponding accumulation and average travel distance, $V_i^m$ is the cruising speed or non-cruising speed of $x$, and $\Delta t$ is the simulation step size. Furthermore, each vehicle family adheres to the mass conservation equation:

$$n_{ij,k}^{x,r}(t_{u+1}) = n_{ij,k}^{x,r}(t_u) + \delta_{ij,k}^{x,r}(u) - o_{ij,k}^{x,r}(u) \tag{4}$$

where $\delta_{ij,k}^{x,r}(u)$ is the input of the vehicle family, including exogenous demand from the regions or transfers from other families, and $o_{ij,k}^{x,r}(u)$ is the outflow of the vehicle family. Figure 1 illustrates the extended multi-pool representation of the network, where flow transfers between different families are indicated.

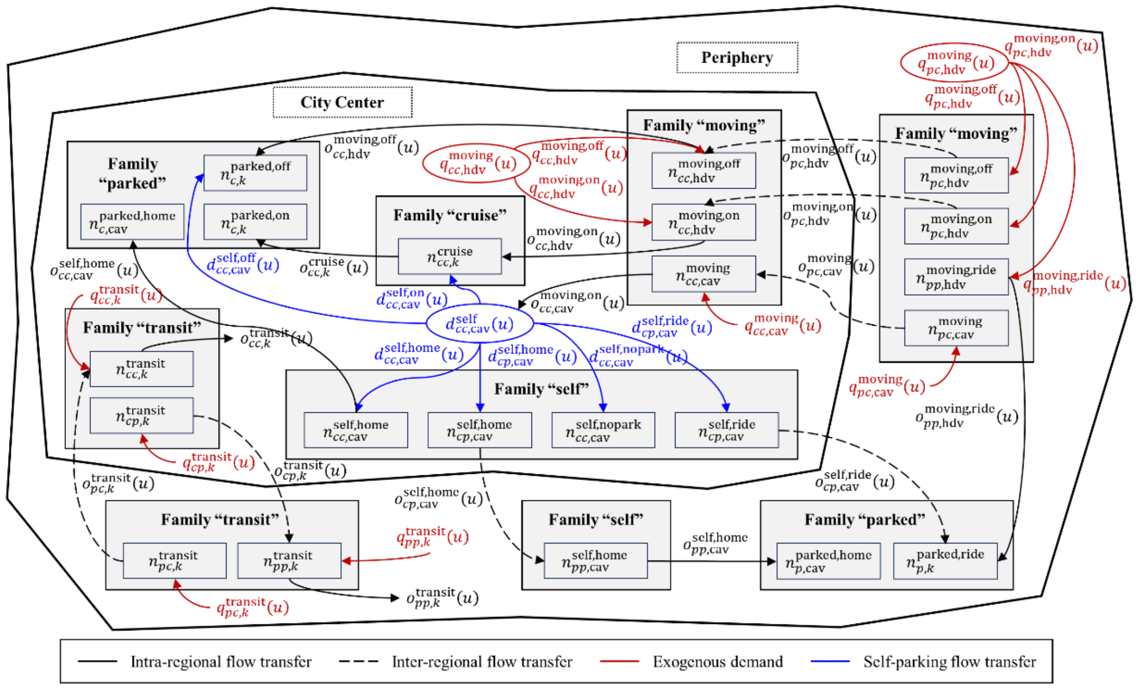


Figure 1 – *Flow transfers between different families of vehicles in the two-region network*

# 3 EXPERIMENTAL RESULTS

An experiment is performed on a two-region mixed autonomy network with park-and-ride based on the Melbourne metropolitan area (see Figure 2a, Shafiei et al., 2023) for demonstration purposes. Under the demand conditions provided in Figure 2b, the temporal evolution of regional accumulation and trip completion rates under initial pricing conditions and optimized park-and-ride parking prices are compared in Figure 2c and d, respectively. With the optimal pricing strategy, congestion in city center is effectively alleviated, leading to a significant reduction in regional accumulation and an improvement in trip completion rates. The proposed two-region model effectively analyzes the impact of P&R and self-parking CAVs on network flow. Moreover, the proposed model is versatile which can be utilized to inform decision-making on various urban parking policies and services for better mobility management in mixed autonomy networks.

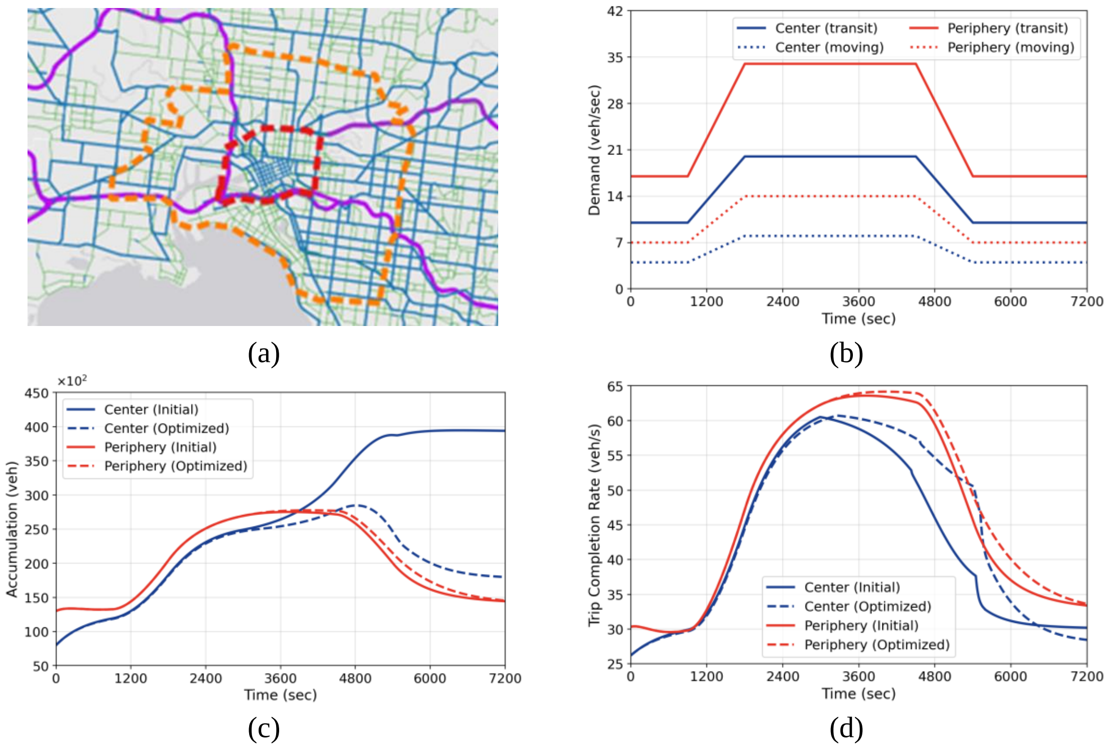


Figure 2 – *(a) Melbourne metropolitan area (red and orange dots outline the city center and the periphery); Temporal evolution of (b) demand, (c) accumulation, and (d) Trip completion rate in different regions.*

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