Dedicated Gating Strategy for Multi-Variate Traffic Flow Streams

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1 INTRODUCTION

Electric Vehicle (EV) technology presents an effective solution to mitigate traffic-induced air pollution in urban areas, especially when paired with green energy production. However, the Market Penetration Rate (MPR) of these vehicles is not expected to surge in the near future, leading to a prolonged period of mixed traffic with both EVs and Regular Vehicles (RVs). Given the uneven distribution of congestion and its related environmental issues across the network, there is a need for innovative traffic management strategies, which prioritize EVs in areas with high levels of congestion and pollution. The concept of the Network-wide Fundamental Diagram (NFD), or Macroscopic Fundamental Diagram (MFD), has enabled transportation planners to develop regional traffic management strategies, including perimeter control (Daganzo, 2007). This method manipulates vehicle flows across urban network regions by adjusting traffic lights at regional boundaries (Geroliminis et al., 2012; Keyvan-Ekbatani et al., 2015). Recent studies have explored perimeter control in mixed traffic scenarios, particularly leveraging data from connected and autonomous vehicles (Yang et al., 2019).

This study introduces an innovative control strategy based on dedicating a portion of the links on the periphery of the network regions, by which the vehicles can transfer between different regions of the network, to EVs, in order to minimize the total time spent by vehicles as well as the vehicular emissions over the network. Unlike existing models that do not differentiate between RVs and EVs in perimeter control, this approach specifically addresses the heterogeneous distribution of traffic and environmental concerns, particularly in Central Business District (CBD) areas, by controlling the accumulations of RVs and EVs in each region in large-scale realistic networks. A Model Predictive Control (MPC) method is used to solve the optimization problem. Also, a mesoscopic traffic simulation tool, DYNASMART-P, is incorporated to the MPC approach to simulate the movement of vehicles throughout the network (Kavianipour et al., 2021). The proposed framework is applied to the city of Chicago network. The main contributions of this study are as follows.

- Providing a framework for optimizing the perimeter control in a mixed traffic of RVs and EVs at large-scale realistic networks to minimize congestion and emission over the network.
- Introducing an innovative control strategy relying on dedicated links.
- Investigating the impacts of different MPRs of EVs on the effectiveness of the perimeter control.

2 RESEARCH FRAMEWORK

This section presents the general framework of the study, which includes three subsections. The first subsection describes the modeling of dynamic traffic system, the second subsection elaborates on the emission estimation based on the NFD, and finally, the last section presents the optimal perimeter control problem in presence of EVs.

2.1 Modeling of Traffic Dynamics

A typical urban city of single-center structure is considered, with two regions $r \in R$, the CBD as $r = 1$ and the outside region as $r = 2$, where the traffic control is implemented at the perimeter between the two regions via signalized intersections. The schematic representation of the travel demands in the two-region network is presented in Figure 1. This study considers two types of vehicles i (RV and EV). The travel demands are denoted based on their origin region x, and destination region y at time t, as $q_{xy}^{i}(t)$. We denote the MPR of each vehicle type i as MPR^{i}. Therefore, $q_{xy}^{i}(t)$, can be calculated as $q_{xy}(t) \times MPR^{i}$.

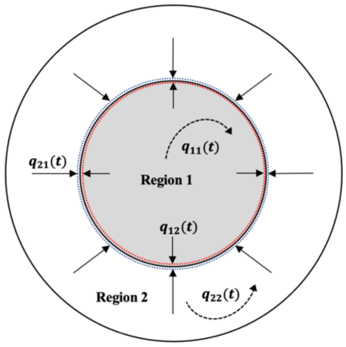


Figure 1 - Schematic representation of the traffic demands in a two-region NFD system

At the network level, the dynamics of the system are described by the NFD, where $G_r(n_r(t))$ is the exit flow function of vehicle accumulation in the region r at time t, $n_r(t)$. The NFD is assumed to be known for each region and is calibrated using to the approach, proposed by Germi (2020). $n_{xy}^{i}(t)$ is defined as total number of vehicles of type i in region x destined to region y at time t. Note that $\sum_y n_{xy}^{i}(t) = n_x^{i}(t)$ and $\sum_i n_x^{i}(t) = n_x(t)$. The transfer flow of vehicle type i from region x to y at time t is derived as below.

$$M_{xy}^{i}(t) = \frac{n_{xy}^{i}(t)}{n_x(t)} \times G_x\big(n_x(t)\big) \tag{1}$$

In order to separately control the transfer flow of RVs and EVs from region 2 to 1, a portion of network links on the perimeter are dedicated to the EVs (Figure 3). The perimeter has N intersections divided into two types: N_d is the number of intersections, dedicated to EV transfers from region 2 to 1, and N_m allow transfers for both EVs and RVs. In this regard, $M_{xy}^{ig}(t)$ is the completed trips by vehicle type i from region x to y at time t, which transferred via intersection type g. The control variables $u_{xy}^{g}(t)$ determine the ratio of transfer flow that transfers from region x to region y at time t via intersection type g, where $0 \leq u_{xy}^{g}(t) \leq 1$. The schematic representation of the transfer and internal flows is illustrated in Figure 2. To estimate $M_{xy}^{ig}(t)$, two distinct path costs are considered, e.g., transferring through dedicated intersections and through regular intersections, as illustrated in Figure 3. Assuming that the vehicles detour to other intersections by moving on the perimeter of region 1, the delay of each path is equal to the time of this detour in addition to the delay that the vehicle experiences at the intersection to transfer between the regions. The average detour length of vehicles to reach the regular intersections (Det^{m}) and dedicated intersections (Det^{d}) can be approximated as below:

$$Det^{m} = \frac{P \times N_d}{4 \times N_m \times N}, \qquad Det^{d} = \frac{P \times N_m}{4 \times N_d \times N} \tag{2}$$

where P is the length of the shared boundary between the two regions. Considering the macroscopic traffic relations, the average detour travel time can be calculated as $\mathcal{T}_{xy}^{g}(t) = Det^{g}/\bar{V}_x(t)$, where $\bar{V}_x(t)$ is the average speed of vehicles in region x at time t. Also, to transfer from region x to y, the average delay at intersections can be estimated as $ID_{xy}^{g}(t) = ((1 - u_{xy}^{g}(t)) \times T_C/2$, where T_C is the cycle time. The logit model is used in this study for modeling the route choice behavior of the vehicles. In this regard, the probability of choosing each path (e.g., regular or dedicated intersection) for the vehicles can be calculated. Regarding transferring from region 1 to 2, the ratio between $M_{12}^{id}(t)$ and $M_{12}^{im}(t)$ can be assumed to be equal to the ratio of the probability of the choosing the paths that goes through dedicated and regular intersections, respectively. Thus:

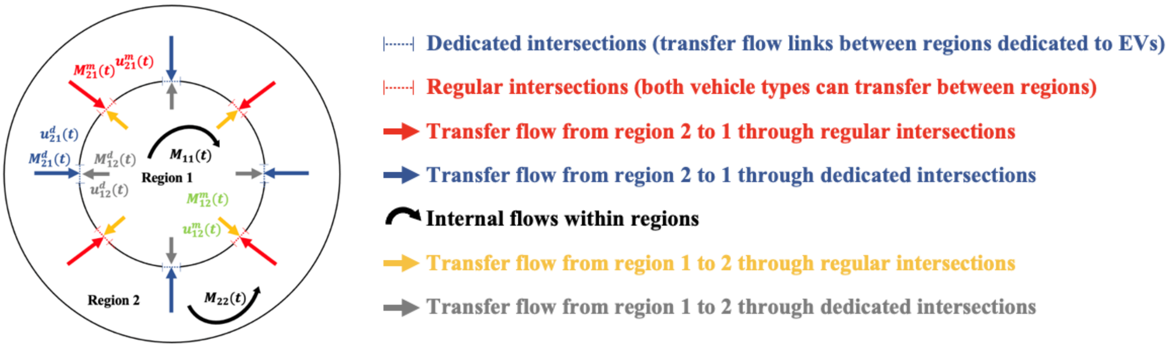


Figure 2 - Schematic illustration of transfer and internal flows and controllers in two-region system

$$M_{12}^{id}(t) = \frac{\exp\left(\mathcal{T}_{12}^{m}(t) + ID_{12}^{m}(t)\right)}{\sum_{g\in G} \exp\left(\mathcal{T}_{12}^{g}(t) + ID_{12}^{g}(t)\right)} \times M_{12}^{i}(t), \qquad M_{12}^{im}(t) = M_{12}^{i}(t) - M_{12}^{id}(t) \tag{3}$$

On the other hand, regarding the transfer from region 2 to 1, as RVs are not allowed to transfer through the dedicated intersections, $M_{21}^{RVd}(t) = 0$ and $M_{21}^{RVm}(t) = M_{21}^{RV}(t)$. Therefore, similarly, $M_{12}^{EVd}(t)$ and $M_{12}^{EVm}(t)$ can be calculated as follows.

$$M_{21}^{EVd}(t) = \frac{\exp\left(\mathcal{T}_{21}^{m}(t) + ID_{21}^{m}(t)\right)}{\sum_{g\in G} \exp\left(\mathcal{T}_{21}^{g}(t) + ID_{21}^{g}(t)\right)} \times M_{21}^{EV}(t), \qquad M_{21}^{EVm}(t) = M_{21}^{EV}(t) - M_{21}^{EVd}(t) \tag{4}$$

2.2 Emission Estimation Based on NFD

To estimate the vehicular emissions in region r at time t, this study utilizes the approach, proposed by Saedi et al. (2020), in which emissions generated at large-scale networks are estimated incorporating the NFD. Thus the $E_r^j(t)$ denoting the generated tons of emission of type $j \in J$ in region r at time t, can be calculated as follows.

$$E_r^j(t) = (\sum_{i\in I} \alpha_r^{ij} \times MPR^i) \times K_r(t) \times (\beta_r^j + V_r(t)) \tag{5}$$

where $K_r(t)$ and $V_r(t)$ are the average density and speed in region r at time t, respectively, and α_r^{ij} and β_r^j are the model parameters that are calibrated using the approach, presented in (12). Here, J is the set of emission types that we consider in this study, which includes carbon dioxide (CO_2), nitrogen oxides (NO_x), volatile organic compounds (VOC), and particulate matters (PM).

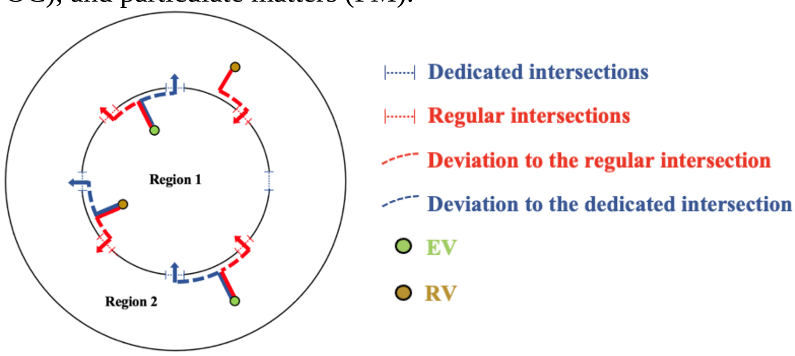


Figure 3 - schematic illustration of the detour of different type of vehicles on the perimeter of the region 2, transferring from region 2 to region 1

2.3 Optimal Perimeter Control in Presence of EVs

This study formulates the cost function, incorporating total time spent in the network, emission, and the total time spent for detour by RVs, that is imposed on these vehicles due to dedicating a portion of intersections on the perimeter of the central region, as follows.

$$Z = \int_{t=0}^{T_S} ([n_1(t) + n_2(t)] \times VOT) + (\sum_{j \in J} [E_1^j(t) + E_2^j(t)] \times C^j) + \mathcal{T}_{21}^m(t) \times u_{21}^m(t) \times M_{21}^{RVm}(k) \times VOT) \tag{6}$$

where T_S is the total simulation time, VOT is the users' average value of time in \$, and C^j is the equivalent cost of the emission type on society in \$ per ton of emission. The first term of the cost function represents the total time spent in the network, the second term estimates the emission cost in the network, and the third term finds the total time spent for detour by RVs to reach a regular intersection on the perimeter. In this optimization framework, the decision variables are the control variables over time, e.g., $u_{21}^m(t)$, $u_{21}^d(t)$, $u_{12}^m(t)$, and $u_{12}^d(t)$.

An MPC approach is used to find optimal control variables to minimize a cost function at each control time step, by solving the optimization model over a moving time horizon of the next H_P control time steps (prediction horizon). In this regard, a mesoscopic traffic simulation tool, DYNASMART-P, is incorporated to simulate the movement of individual vehicles throughout the network (Fakhrmoosavi et al., 2022). This tool finds the network user equilibrium by assigning the vehicles to their shortest paths iteratively and provides the vehicle trajectories over the network. The control process is graphically demonstrated in Figure 4. The inputs of the MPC controller are the traffic demands and accumulations at the previous control time step $\hat{n}_{xy}^i(k_c - 1)$ and $\hat{q}_{xy}^i(k_c - 1)$.

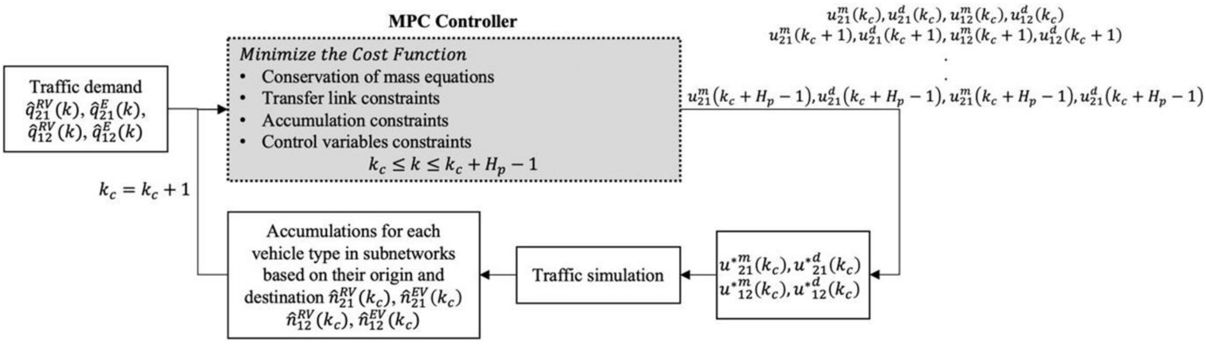
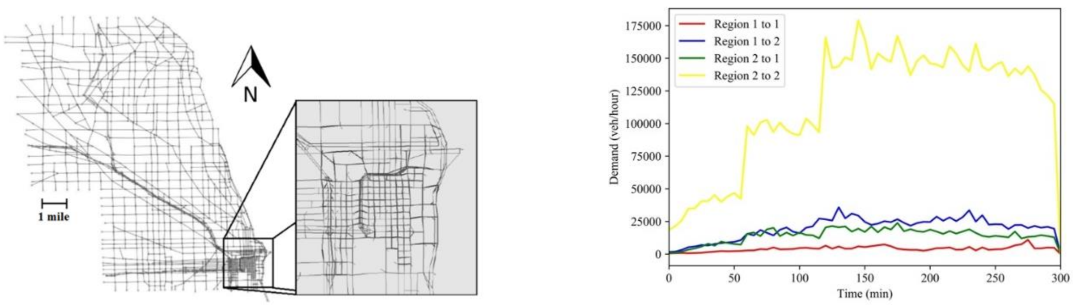


Figure 4 - Control diagram for MPC approach

3 CASE STUDY

The proposed framework of this study is applied on the large-scale network of Chicago with 1,578 nodes, 4,805 links, and 218 traffic analysis zones. The simulation horizon is the AM peak period (5:00 AM to 10:00 AM plus two hours of simulation to unload the network). The number of vehicles simulated in the network is about 760,000. The Chicago CBD is defined as the central region in the two-region system. The network configuration and demand profiles are illustrated in Figure 5.



(a) (b)

Figure 5 - Chicago city network and its downtown region; and (b) regional demand profiles

The congestion and emission over the network are compared with and without perimeter control scenario and also a perimeter control without differentiating between RVs and EVs scenario. Different scenarios for MPRs of EVs from 0% to 100% with the increment of 10% are also considered to evaluate the effects of different EV MPRs on the performance of the perimeter control.

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