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A hierarchical urban network control with integration of demand balance and traffic signal coordination ⋆

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Abstract: This paper concerns the integration of demand balance control and traffic flow coordination control in a hierarchical framework for complex urban traffic networks. At the first level, a complex traffic network is first partitioned into several subnetworks. The traffic dynamics in each subnetwork is modeled by utilizing the concept of Macroscopic Fundamental Diagram (MFD), which relates the network-wide space-mean flow and the number of vehicles at the aggregated level. This model aims at designing a demand balance model predictive controller (MPC), which can improve the internal flow inside the subnetwork by regulating the input flows from outside. At the second level, based on a more detailed traffic flow model, the signal timings of all intersections for each subnetwork are determined by a flow coordination MPC controller, which aims at distributing the number of vehicles in each subnetwork as homogeneously as possible. The effectiveness of the proposed approach is investigated via simulation under different scenarios on a hypothetical urban traffic network, and the performance is compared with other control strategies.

Keywords: Urban traffic networks, model predictive control, demand balance control, traffic flow coordination, macroscopic fundamental diagram.

1. INTRODUCTION

Traffic congestion in modern cities is still a major problem for human society, due to the limited transportation infrastructures available, the high demand for travelling, and the unpredictable activities of travelers. It leads to a lot of social and economic problems, such as environment pollution, traffic accident and increased cost of living. Therefore, many methodologies have been developed for congestion governance. From a long-term perspective, network-wide traffic signal control is an efficient way to mitigate traffic jams and to improve the mobility of the whole network by regulating traffic behaviors.

The scale of real road networks in big cities are usually large, and the dynamics of traffic flow are too complex. With respect to control of such large-scale, complex, dynamic systems with multiple-inputs and multiple-outputs, it is a big challenge to develop an effective and feasible strategy to address traffic congestion and propagation. Fortunately, parallel control theory (PCT) proposed by Wang (2010), which is composed of Artificial Societies (A), Computational Experiments (C), and Parallel Execution (P), or named as ACP method, provides a more tractable way to solve the aforementioned problems. In this framework, an artificial traffic system is built in terms of real road network, while computational experiments can be carried out within the system. A real traffic network runs in parallel with its artificial network, and implements the optimal control policies received from the artificial network through real-time communication. This framework paves the way for designing appropriate control strategies and meeting the multiple-objective requirements in urban traffic control at different levels, such as traffic demand level, subnetwork coordination level and intersection control level.

More recently, the concept of MFD is widely used for control of large-scale urban traffic networks from an aggregated point of view. Its existence was observed and verified by Geroliminis and Daganzo (2008) based on experimental data. An MFD links the number of vehicles (or densities) and the space-mean traffic flow in the network. If an urban traffic network is considered as a whole, the MFD can describe the macroscopic characteristics of the network. On the one hand, these findings make it easier to model the dynamics of traffic flow at the network level; on the other hand, researchers can design real-time control strategies based on the MFD to mitigate congestion and improve mobility in large-scale urban traffic networks. Geroliminis et al. (2013) proposed optimal perimeter control for a two-region urban city based on the MFD by regulating the exchanged traffic flows on the perimeter borders between the two regions. Perimeter and boundary control for multiple regions in heterogeneous urban

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traffic networks has also been investigated by Aboudolas and Geroliminis (2013). Moreover, a mixed control strategy integrating perimeter control for urban roads and ramp metering for freeways has been developed by Haddad et al. (2013), and a hybrid control approach incorporating perimeter controllers and switching signal timing plans controllers has been introduced for urban traffic networks by Hajiahmadi et al. (2015). Keyvan-Ekbatani et al. (2015) also proposed a multiple concentric-boundary feedback gating strategy by adjusting the inflow ratio of different regions of an urban network to prevent the protected urban region from congestion and to improve the mobility within the region. These strategies mentioned above tried to develop the control approaches from an macroscopic point of view by manipulating two components: the input traffic flows from outside of the network (perimeter control) and the inter-transfer flows between neighborhood subnetworks (boundary control). However, it might be faced while implementing boundary control among subnetworks that there is no enough space between directly connected subnetworks to store the restricted vehicles, resulting in vehicles queuing on the boundary, due to the control actions executed.

In this paper, we mainly focus on dealing with the traffic demands control problem and the traffic signals coordination control problem in a two-level hierarchical framework for complex urban traffic networks, which belongs to the computational experiment in the ACP method. At the first level, based on decomposing a complex traffic network into several subnetworks, a demand balance controller is developed by utilizing an improved MFD-based subnetwork model. This level aims at keeping the number of vehicles of each subnetwork around a desired point by regulating the proportion of the input traffic demands at the periphery of the whole network. At the second level, a more detailed model is adopted to describe the dynamics of traffic flow in each subnetwork, and then the traffic signals coordination control problem is formulated. This level aims at smoothing traffic movements and distributing the congestion evenly within these subnetworks through obtaining the optimal control plan for each intersection. Finally, all the optimization problems are embedded in a rolling horizon framework, i.e. model-based predictive control (MPC), for the application in practice.

The rest of this paper is organized as follows. In Section 2, a demand balance MPC controller based on the MFD-based multi-subnetwork model is designed. In Section 3, the model-based control problem of coordination of traffic signals is formulated. The performance of the proposed approach is evaluated in a typical complex traffic network in Section 4. Section 5 concludes this paper.

2. DEMAND BALANCE MPC CONTROLLER

In order to balance the traffic demand for complex urban traffic networks, an aggregated traffic model that can describe the dynamic behavior of the traffic system is needed for the MPC optimization problem. The concept of MFD provides a tractable way for this modeling as it reveals a unimodal, low-scatter relationship between the number of vehicles and the outflow at the network level. Therefore, based on some partition methods proposed by Ji and Geroliminis (2012) and Zhou et al. (2012), a large-scale heterogeneous traffic network can be divided into several homogeneous subnetworks with a well-defined MFD. In the following, an extension of MFD-based subnetwork model inspired by Geroliminis et al. (2013) is introduced, and then the corresponding MPC problem is able to be formulated.

Consider a complex urban traffic network with N subnetworks, and denote by $i = 1,2,...,N$ a subnetwork in the system. Let us assume that each subnetwork has a well-defined MFD. Therefore, a solid relationship between the number of vehicles $N_i(k_u)$ and the network flow $M_i(k_u)$ is established

$$M_i(k_u) = G_i(N_i(k_u)) \tag{1}$$

where $N_i(k_u)$ is the number of vehicles in subnetwork i at time step k_u, $G_i(\cdot)$ is the function of MFD. In subnetwork i, the total number of vehicles $N_i(k_u)$ at time step k_u is conceptually separated into two parts: the number of vehicles intending to stay inside the subnetwork, $N_{ii}(k_u)$ and the number of vehicles intending to go to subnetwork j, $N_{ij}(k_u)$, where $j \in \mathcal{N}_i$ and $\mathcal{N}_i$ is the set of subnetworks in the neighborhood of subnetwork i. Therefore, they are updated by the following discretized conservation equations:

$$\begin{aligned} N_{ii}(k_u+1) &= N_{ii}(k_u) + T_u[d_{ii}(k_u) + \sum_{j\in\mathcal{N}_i} p_{ii}(k_u)M_{ji}(k_u) - M_{ii}(k_u)] \\ N_{ij}(k_u+1) &= N_{ij}(k_u) + T_u[d_{ij}(k_u) + \sum_{j\in\mathcal{N}_i} p_{ij}(k_u)M_{ji}(k_u) - M_{ij}(k_u)] \end{aligned} \tag{2}$$

where similarly the traffic demand for subnetwork i is also expressed separately by $d_{ii}(k_u)$ and $d_{ij}(k_u)$, the traffic demand intending to stay in subnetwork i at time step k_u, and the traffic demand for subnetwork i at time step k_u intending to go to subnetwork j ($j \in \mathcal{N}_i$); T_u is the sample time interval, $M_{ji}(k_u)$ is the traffic flow getting into subnetwork i from subnetwork j at time step k_u, and $M_{ij}(k_u)$ is the traffic flow leaving subnetwork i for subnetwork j; $p_{ij}(k_u)$ represents the one step transition probability of the traffic flow transferring from subnetwork i to j at time step k_u, while is the proportion of the traffic flow in the total network traffic flow intending to different destinations. Therefore, we have

$$p_{ii}(k_u) + \sum_{j\in\mathcal{N}_i} p_{ij}(k_u) = 1 \tag{3}$$

which illustrates that the sum of the one step transition probabilities for traffic flows leaving subnetwork i equals 1. By multiplying the one step transition probability, the transferring traffic flows can be obtained from the network traffic flow of subnetwork i, as

$$\begin{aligned} M_{ii}(k_u) &= p_{ii}(k_u)M_i(k_u) \\ M_{ij}(k_u) &= p_{ij}(k_u)M_i(k_u) \end{aligned} \tag{4}$$

which means that the network traffic flow of subnetwork i is divided into the traffic flow intending to stay in the subnetwork and the traffic flow intending to leaving for neighboring subnetworks.

The total number of vehicles in subnetwork i can be updated by

$$N_i(k_u) = N_{ii}(k_u) + \sum_{j\in\mathcal{N}_i} N_{ij}(k_u) \tag{5}$$

and the one step transition probabilities can be estimated by

$$p_{ii}(k_u) = \frac{N_{ii}(k_u)}{N_i(k_u)}, \quad p_{ij}(k_u) = \frac{N_{ij}(k_u)}{N_i(k_u)} \tag{6}$$

Similarly, the traffic demand for subnetwork i can be calculated by

$$d_i(k_u) = d_{ii}(k_u) + \sum_{j\in\mathcal{N}_i} d_{ij}(k_u) \tag{7}$$

which is the sum of the traffic demand intending to stay in subnetwork i and the traffic demand intending to leave subnetwork i for the neighboring subnetworks. In addition, the transferring