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Integration of Regional Demand Management and Signals Control for Urban Traffic Networks

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ABSTRACT Many efforts have been focused on the network-wide traffic signal optimization to deal with the congestion problem in big cities. Nevertheless, research evidence illustrates that both improper traffic network managements and excessive traffic demands are the key factors leading to the oversaturated traffic conditions. Current studies encounter the bottleneck in addressing the multi-objective optimization problem. This point calls for designing the hierarchical control framework. In this paper, we concern a two-level hierarchical model-based predictive control scheme to improve mobility in heterogeneous large-scale urban traffic networks, so as to mitigate traffic jams. On the basis of a network partition, a regional demand management approach regulating the input traffic flow from adjacent regions is proposed for multi-subnetworks management taking the advantage of the concept of a macroscopic fundamental diagram of urban traffic networks. This can be viewed as a higher level control layer and can be integrated with other strategies. The lower level control layer utilizes the traffic signals coordination within the subnetworks based on a detailed link-level traffic model to optimize the allocation of vehicles in each subnetwork as homogeneous as possible. The simulation results show that integrating regional demand management with a local traffic responsive control into a hierarchical framework can significantly improve the whole network performance under different traffic scenarios in comparison with other available control strategies.

INDEX TERMS Urban traffic networks, hierarchical framework, regional demand management, traffic signals coordination, model predictive control.

I. INTRODUCTION

As the number of vehicles keeps on increasing and the scale of cities expands rapidly, growing urban traffic congestion is a serious problem faced by cities around the world. Traffic congestion results in a large amount of economic and environmental losses to whole society. Traditional solutions considered mainly focus on increasing network capacity and expanding public transport offerings from traffic supply governance point of view. With the development of communication, computing and control technologies for intelligent transportation systems (ITS), adopting network-wide traffic signal control strategies is an efficient way to mitigate traffic jams and to improve the mobility of the whole network by regulating vehicle movements.

In the real world, an urban traffic network composed of thousands of interactive links and signalized intersections is a typical large-scale system. The unpredictable activities of travelers make the dynamics of such a system more complex. With respect to control of urban traffic networks, developing an effective and feasible strategy is still a big challenge for addressing traffic congestion problem on the basis of the available transportation infrastructures. Fortunately, in recent years, cyber-physical systems (CPS) provide a technically feasible solution for networked systems management and control [1]. In this framework, the first and the important step is to establish an artificial traffic model to describe the dynamics of traffic flows in urban

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networks. Then, the model-based control strategies can be designed to regulate the link flows by adjusting the signal timing plans at the intersections. Based on the well-known store-and-forward model, traffic-responsive urban control (TUC) was proposed to manage and control the urban traffic networks in [2]. They presented a multi-variable feedback regulator approach to obtain the optimal signal timings by using the off-line feedback regulator based on the current traffic measurements. In order to make this strategy use on-line, Aboudolas *et al.* [3] further proposed an model predictive control (MPC) approach by embedding the quadratic-programming problem into a rolling-horizon control scheme. Zhang and Zhou [4] proposed a bi-level optimization strategy of signal cycles, offsets and green ratios on the cloud computing platform. In this framework, the coordination control layer optimizes the public cycle for each subnetwork and the offsets of adjacent intersections, and the distributed control layer optimizes the green ratios in each signal cycle on the basis of optimized public cycles and offsets. Delis *et al.* [5] proposed a novel adaptive cruise control for traffic flow dynamics based on a gas-kinetic traffic flow model. Ma *et al.* [6] developed a coordinated signal control system for urban ring roads under vehicle-infrastructure connected environment. In this approach, the signal timing parameters such as cycle length, green split, and offset, could be adjusted based on a heuristic algorithm. Many other works utilized distributed structure to coordinate the signal splits in urban traffic networks [7]–[12]. Although TUC can be applied in practice [13], it may not address the congestion problem at the oversaturated conditions because of the simple of the traffic model. Lin *et al.* [14], [15] designed an MPC controller based on a more accurate urban traffic model fully considering the various traffic scenarios. Ye *et al.* [16] developed a stochastic expected value traffic model and proposed a hybrid intelligent algorithm to solve the stochastic MPC problem. Unfortunately, they have to make a tradeoff between the accuracy of modeling and the computational complexity.

In the recent years, the concept of macroscopic fundamental diagram (MFD) is proposed to model and control large-scale urban traffic networks at an aggregated level. Based on the field data in Yokohama (Japan), the existence of MFD was observed and verified in [17]. An well-defined MFD with unimodal and low scatter of flows for the same number of vehicles is shown in Fig. 1, which establishes a static relationship between the space-mean traffic flow and the number of vehicles (or densities) in the network. If we aggregate the traffic state variables by means of weighed average approach in an urban area, the macroscopic dynamic characteristics of the regional traffic flow can be described by the MFD-based model. These findings pave the way for controlling the road networks from an macroscopic point of view, so as to mitigate traffic jams and to improve vehicle movements in large-scale urban traffic networks. For single-region cities, several studies have developed different control approaches on the basis of the MFD to restrict the inflows along the perimeter of an urban network to make sure that the number

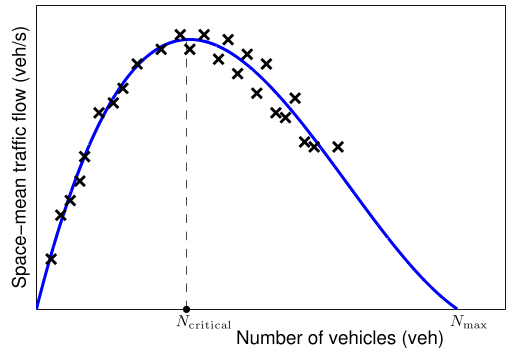

FIGURE 1. Well-defined MFD.

of vehicles within the region does not exceed its critical point, such as bang-bang control [18], proportional-integral (PI) control [19], robust control [20], PI with data-driven adaptive control [21] and so on. For multi-region cities, the main idea is to manipulate the transfer flows between adjacent regions to prevent all sub-networks from oversaturated conditions. Geroliminis *et al.* [22] used an MPC approach to regulate the exchanged traffic flows on the perimeter borders between two urban regions. Aboudolas and Geroliminis [23] investigated the combined perimeter and boundary control for multiple regions by designing a multivariable feedback regulator in heterogeneous urban traffic networks. Keyvan-Ekbatani *et al.* [24] 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. Moreover, recent works also attempt to develop mixed control strategies where not only the ground network dynamics but also other traffic modal has been taken into account, such as mixed control strategy integrating perimeter control for urban roads and ramp metering for freeways in [25], hybrid control approach incorporating perimeter controllers and switching signal timing plans controllers for urban traffic networks in [26], combined vehicular flow and passenger flow dynamics management using three-dimensional fundamental diagram for bi-modal urban networks [27], integrated economic MPC with perimeter control and regional route guidance [28] and so on. More other control strategies with the utilization of MFD can be found in [29]. The most efforts reported in the literature are to design different control approaches by manipulating two elements: the input traffic flows from outside of the network (perimeter control) and the inter-transfer flows between neighborhood subnetworks (boundary control). However, the disadvantage of implementing perimeter and boundary control is that they neglected the impact of link traffic flows on the regional dynamic features. Zhou *et al.* [30] designed a two-level control framework that computes the optimal exchanged flows at the upper level and then sends the targets to the lower level for tracking. It performs worse in the oversaturated scenarios because the large volume of traffic demand cannot be managed or controlled by the high-level controller. Although

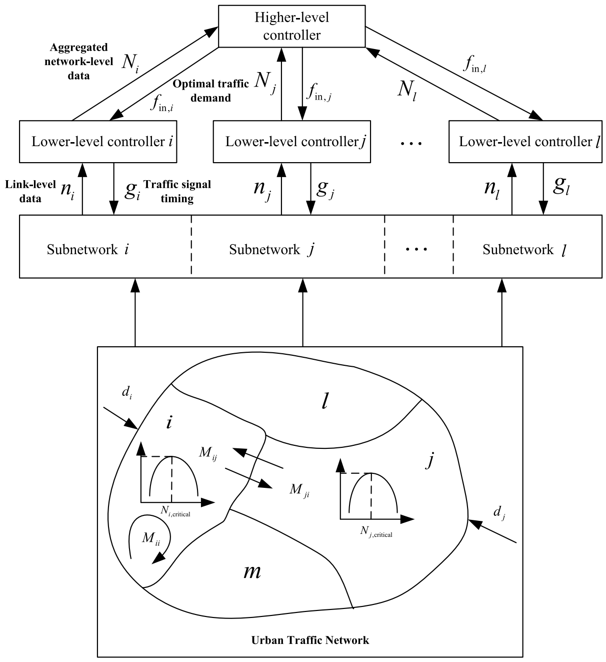

FIGURE 2. The integrated hierarchical control framework.

Zhou *et al.* [31] proposed a hierarchical control structure for restricting the inflows and coordinating the signals, they did not discuss the influences of boundary control that imposed on the exchange flows between neighbors.

Therefore, integrating the MFD-based control and the TUC control in a hierarchical framework could tackle the problems described above. On the one hand, this strategy is able to make the macroscopic traffic state keep a good performance from the network level point of view. On the other hand, it can create a more homogeneous distributions within the network by regulating the vehicular movements. In this paper, we mainly focus on establishing a two-level hierarchical structure for control of complex urban traffic networks, which is consistent with the concept of CPS methodology (see Fig. 2). At the higher-level, on the basis of partitioning a large-scale traffic network into several subnetworks with well-defined MFDs, the aggregated dynamics of traffic flow within each subnetwork is described with an improved MFD-based model. A regional demand management approach is presented to prevent the macroscopic traffic state falling into the congested part of MFD by operating the proportion of input traffic demands at the periphery of subnetwork. Here, the demand management means to design a controller, which carries out the optimization by using the aggregated data to obtain the timing plans for the peripheral traffic signals, and then sends the optimized traffic demands to the lower-level controller as the input traffic flows. At the lower-level, a traffic signals coordination optimization problem based on a more detailed link-level traffic model is formulated to obtain the optimal timing plan for each signalized intersection, so as to smooth vehicular movements and to make the vehicular distribution inside each subnetwork as homogeneously as possible. The rolling horizon framework of MPC [32] enables the proposed method to be applied in practice, which has been widely used in operation planning of high speed trains [33], cooperative vehicle safety systems [34] and signal coordination control system for urban roads [35]. Finally, the benefits of the integrated control approach is demonstrated through simulations.

To summarize, the main contributions of this paper are two-fold: (1) We develop a regional demand management strategy for inflows (including the inter-transfer flows among subnetworks and the input flows from external regions) governance and a traffic signals coordination control strategy for flow regulation in large-scale urban traffic networks, whereby the regional features of subnetworks are explicitly modeled with the utilization of MFD and the dynamic features of links are described with an improved traffic flow control model. (2) We propose an integrated approach to control the whole network by combining the regional demand management and the traffic signals coordination control with a two-level hierarchical structure. The advantage of our strategy is that it can improve the total performance of the system from macroscopic network level to mesoscopic link level.

The remainder of this paper is organized as follows. In Section 2, an improved MFD-based multi-subnetwork model is proposed, and then is used to design the demand management MPC controller at the higher-level. The subnetwork traffic signals coordination control problem at the lower-level is formulated in Section 3. Section 4 evaluates the performance of the proposed approach by using two case studies with different scenarios in a typical complex traffic network. Section 5 concludes this paper and outlines future work.

II. REGIONAL DEMAND MANAGEMENT

In this section, we focus on designing the demand management MPC controller at the higher-level. The higher-level controller can adjust green ratios of traffic lights at the periphery intersections of subnetworks to control or restrict input traffic flows from outside. It has been investigated that the MFD has three characteristics at the network level [36]: (1) the number of vehicles (or mean vehicle density) and the space-mean flow in an urban region exhibit a unimodal and low-scatter relationship under certain conditions; (2) the outflow (or trip completion flow) of the traffic network is a constant proportion of the space-mean flow within the network; (3) the shape of the MFD is insensitive to the traffic demand but is dependent on the topology of the network and the adopted control strategy. These features provide a tractable way for describing the macroscopic dynamic behavior of traffic network and building an aggregated traffic model. Therefore, on the basis of some network decomposition algorithms presented in [37]–[39], a large-scale heterogeneous urban traffic network is able to be divided into several homogeneous subnetworks with an explicit MFD. In the following, an improved and extended MFD-based subnetwork model is introduced as the prediction model of subnetwork MPC controllers, and then the corresponding demand management MPC optimization problem can be formulated.

Consider an urban traffic network with heterogeneous distribution of number of vehicles, consisting of N homogeneous subnetworks, as shown in Fig. 2. Each subnetwork is assumed to have a well-defined outflow MFD. Therefore, we can establish a static relationship between the network outflow (trip completion flow) $M_i(k_u)$ and the number of vehicles $N_i(k_u)$ using the traffic measurements at each time step k_u in subnetwork i ($i \in N$) via the following function

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

where $G_i(\cdot)$ represents the function of MFD. It should be noted that this function could be obtained by using a polynomial fitting method (the same as the approximation in [22]). According to the different destinations of traffic flow, the total number of vehicles $N_i(k_u)$ in subnetwork i at time step k_u is the sum of two components, i.e., the number of vehicles $N_{ii}(k_u)$ denoting their trips from subnetwork i with destination subnetwork i, plus the number of vehicles $N_{ij}(k_u)$ denoting their trips from subnetwork i with destination subnetwork j, where $j \in \mathcal{N}_i$, and $\mathcal{N}_i$ is the set of subnetworks sharing a common boundary with subnetwork i, i.e., its neighbors. Therefore, the dynamic evolution of aggregated traffic flows in subnetworks i can be described by the following discrete conservation equations:

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

where T_u is the sample interval, $d_{ii}(k_u)$ and $d_{ij}(k_u)$ are corresponding to the traffic demand going to destination subnetwork i and the traffic demand going to destination subnetwork j, at time step k_u, respectively; $M_{ji}(k_u)$ is the transfer flow from subnetwork j entering to subnetwork i at time step k_u, $M_{ii}(k_u)$ is the exit flow leaving subnetwork i at time step k_u and $M_{ij}(k_u)$ is the transfer flow leaving subnetwork i to subnetwork j; $p_{ij}(k_u)$ is the one-step transition probability of transfer flow from subnetwork i with destination to subnetwork j at time step k_u, which also represents the proportion of traffic flow going to different destinations in the total network traffic flow. Hence, we have

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

which means that the sum of one-step transition probabilities of outflows for subnetwork i is equal to 1. It should be noted that the one-step transition probability refers to two directly connected subnetworks. With the utilization of the one-step transition probability, we can obtain the transfer flows with different destinations of subnetwork i,

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

which shows that the network outflow M_i of subnetwork i is decomposed into the traffic flows terminating their trips within the subnetwork and the traffic flows going to its neighbors. These equations are a generalized (several subnetworks instead of two) equations presented in [22].

If the real-time traffic measurements in subnetwork i at time step k_u are able to be obtained from the detectors equipped in all links, we have

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

and the one-step transition probability for each destination is estimated via

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

It should be noted that the one-step transition probability is time dependent due to the variation of traffic state in each subnetwork.

The total traffic demand for subnetwork i at time step k_u is the sum of traffic demand for different destinations, which can be calculated by

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

In addition, the traffic flow transferring to subnetwork i through the boundary from its neighbor subnetworks is

$$t_i(k_u) = \sum_{j\in\mathcal{N}_i} M_{ji}(k_u) \tag{8}$$

Then, the total traffic inflow for subnetwork i is the sum of traffic demand from external regions and the transfer flow from its neighbor subnetworks to destination subnetwork i

$$f_{\text{in},i}(k_u) = d_i(k_u) + t_i(k_u) \tag{9}$$

Lin *et al.* [40] investigated the existence of the network traffic flow equilibria based on simulation experiments and analysis. They demonstrated that if the network inflow generated from adjacent regions exceeds a critical value, i.e., its equilibria point, the space-mean traffic flow of the entire network will deteriorate, resulting in oversaturated condition or gridlock. It is necessary to regulate the input flow to guarantee the maximum space-mean flow inside the traffic network. With the utilization of the MFD-based traffic model mentioned above, we can design an MPC controller to management the traffic demand among all subnetworks at the higher-level. Since our goal is to maximize the output traffic flow of each subnetwork, i.e., the sum of traffic flows leaving all subnetworks, the aim of this controller is to prevent the aggregated traffic state within each subnetwork falling into its congested part of MFD by regulating the proportion of input traffic demands at the periphery of subnetworks, so as to improve the system performance from the perspective of network level. Therefore, the overall optimization problem of the demand management MPC at the higher-level is formulated as follows:

$$
\begin{aligned}
\min_{r_i(k_u)} J_u &= \sum_{p=0}^{N_p^u-1} \sum_{i \in N} [\max(0, N_i(k_u+p) - N_{i,\text{critical}})]^2 \\
&= \sum_{p=0}^{N_p^u-1} \sum_{i \in N} [\max(0, N_{ii}(k_u+p) \\
&\quad + T_u[r_i(k_u+p)\tilde{d}_{ii}(k_u+p) \\
&\quad + r_i(k_u+p) \sum_{j \in \mathcal{N}_i} p_{ii}(k_u+p) M_{ji}(k_u+p) \\
&\quad - M_{ii}(k_u+p)] \\
&\quad + N_{ij}(k_u+p) + T_u[r_i(k_u+p)\tilde{d}_{ij}(k_u+p) \\
&\quad + r_i(k_u+p) \sum_{j \in \mathcal{N}_i} p_{ij}(k_u+p) M_{ji}(k_u+p) \\
&\quad - M_{ij}(k_u+p)] - N_{i,\text{critical}})]^2 \\
\text{s.t. } & \text{Subnetwork model } (1)-(9) \\
& f_{\text{in},i}(k_u+p) = r_i(k_u+p)\tilde{f}_{\text{in},i}(k_u+p) \\
& r_{i,\min} \le r_i(k_u+p) \le r_{i,\max} \\
& 0 \le N_i(k_u+p) \le N_{i,\text{jam}} \\
& \text{for } p = 0, \ldots, N_{\text{p}}^u - 1, \text{ for all } i \in N
\end{aligned} \tag{10}
$$

where N_p^u is the prediction horizon of MPC, the control time interval is set to be T_u, the control variable $r_i(k_u+p)$ is the ratio of traffic demands allowed to enter the subnetwork i, which is optimized to manipulate the input traffic demands, $r_{i,\min}$ and $r_{i,\max}$ are the lower and upper bounds for $r_i(k_u+p)$ respectively, $N_{i,\text{jam}}$ is the number of vehicles at the jammed density in subnetwork i, $\tilde{f}_{\text{in},i}$ is the input traffic demand from external and neighboring regions, which can be estimated via historical traffic data. The higher-level controller carries out the optimization to obtain the optimal value of r_i, which can be used to compute the green time length of the peripheral traffic signals by $g_{\text{peri},i}(k_u) = r_i(k_u)c_{\text{cycle}}$, and also sends the optimized traffic demands to the lower-level controller as the input traffic flows of each subnetwork according to $f_{\text{in},i}(k_u+p) = r_i(k_u+p)\tilde{f}_{\text{in},i}(k_u+p)$.

III. TRAFFIC SIGNALS COORDINATION

In this section, we focus on designing the traffic signals coordination MPC controller for each subnetwork at the lower-level. The lower-level controller can adjust green ratios of traffic lights at the intersections within each subnetwork to coordinate or control traffic flows on road links. A link level urban traffic model proposed in [14], i.e. S model, is selected as the prediction model of MPC, because it is capable of describing the dynamic process of link flow in detail, especially the oversaturated traffic situation. Based on the S model and the real-time traffic measurements, the optimal traffic signal timing plans for all intersections within each subnetwork can be obtained to coordinate the traffic flows in links.

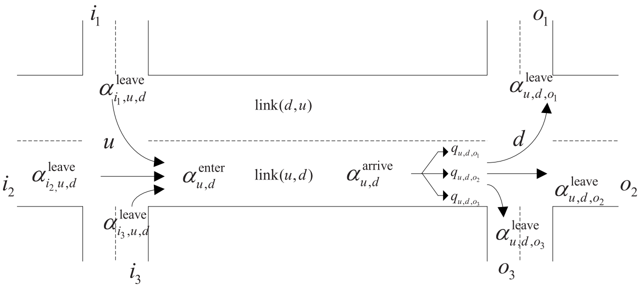

FIGURE 3. A typical link between two adjacent intersections.

This controller can not only smooth the vehicular movements within the subnetwork, guaranteeing the homogeneous vehicle distributions across the subnetwork, but also reduce the risk of oversaturation and traffic delays.

As the same with other mesoscopic urban traffic models, the S model mainly focus on revealing the vehicular flow dynamics in the link. According to the conservation equation for vehicles in a typical urban link $(u, d) \in \mathcal{L}$ shown in Fig. 3 we have

$$
n_{u,d}(k_l+1) = n_{u,d}(k_l) + (\alpha_{u,d}^{\text{enter}}(k_l) - \alpha_{u,d}^{\text{leave}}(k_l)) \cdot c_{\text{cycle}} \tag{11}
$$

where $u \in \mathcal{E}$ and $d \in \mathcal{E}$ are the upstream and downstream intersections for link (u, d), $\mathcal{L}$ and $\mathcal{E}$ are the set of links and intersections in the network respectively, $\alpha_{u,d}^{\text{enter}}(k_l)$, $\alpha_{u,d}^{\text{arrive}}(k_l)$ and $\alpha_{u,d}^{\text{leave}}(k_l)$ denote the entering, arriving and leaving flows in link (u, d) at time step k_l, $q_{u,d}(k_l)$ is the queue length in link (u, d), c_{cycle} is the cycle time of traffic signal (here it is set to be equal to the sample interval T_l for all intersections). It should be noted that the entering and leaving flows for link (u, d) are separately the sum of traffic flows moving from its upstream links and traffic flows moving to its downstream links:

$$
\begin{aligned}
\alpha_{u,d}^{\text{enter}}(k_l) &= \sum_{i \in I_{u,d}} \alpha_{i,u,d}^{\text{enter}}(k_l) \\
\alpha_{u,d}^{\text{leave}}(k_l) &= \sum_{o \in O_{u,d}} \alpha_{u,d,o}^{\text{leave}}(k_l)
\end{aligned} \tag{12}
$$

The leaving traffic flow for each downstream intersection is determined by

$$
\begin{aligned}
\alpha_{u,d,o}^{\text{leave}}(k_l) = \min(&\beta_{u,d,o}(k_l) \cdot \mu_{u,d} \cdot g_{u,d,o}(k_l)/c_{\text{cycle}}, \\
& q_{u,d,o}(k_l)/c_{\text{cycle}} + \alpha_{u,d,o}^{\text{arriv}}(k_l), \\
& \beta_{u,d,o}(k_l)(C_{d,o} - n_{d,o}(k_l))/c_{\text{cycle}})
\end{aligned} \tag{13}
$$

where its value depends on the minimum of three terms, i.e., the capacity of downstream intersection corresponding to the saturated traffic condition, the waiting and arriving flows corresponding to the undersaturated traffic condition and the available space of downstream link corresponding to the oversaturated traffic condition. Moreover, $\beta_{u,d,o}(k_l)$ is the turning rate, $\mu_{u,d}$ is the saturation flow, $g_{u,d,o}(k_l)$ is the green time ratio, $C_{d,o}$ is the maximum number of vehicles that the downstream link (d, o) can hold, the queuing vehicles with destination o is calculated by

$$q_{u,d,o}(k_l+1) = q_{u,d,o}(k_l) + (\alpha^{\text{arriv}}_{u,d,o}(k_l) - \alpha^{\text{leave}}_{u,d,o}(k_l)) \cdot c_{\text{cycle}} \tag{14}$$

the arriving vehicles with destination o is updated by

$$\alpha^{\text{arrive}}_{u,d,o}(k_l) = \beta_{u,d,o} \cdot \alpha^{\text{arrive}}_{u,d}(k_l) \tag{15}$$

For more information about this model, the reader is referred to [14] and [15].

It should be noted that as a dynamic flow model, this model is able to depict all the situations that might occur in real urban traffic roads, due to the fact that the equation (13) calculating the average leaving traffic flow takes three different traffic scenarios into account. However, when this model is considered as a control model in the optimization problem of MPC, this operation brings a high level of computational complexity. Therefore, in order to make this model more suitable for control, an appropriate simplification from the optimization point of view has to be developed. In the oversaturated situation, the average leaving traffic flow is determined by the rate that the downstream link can accommodate. Consider that the total mumbler of vehicles in a road will not exceed its maximum capacity in reality, i.e. no vehicle from the upstream links is permitted to enter the link when its storage spaces are completely occupied, the third term in (13) can be removed from this model

$$\begin{aligned}\alpha^{\text{leave}}_{u,d,o}(k_l) = \min(&\beta_{u,d,o}(k_l) \cdot \mu_{u,d} \cdot g_{u,d,o}(k_l)/c_{\text{cycle}},\\ &q_{u,d,o}(k_l)/c_{\text{cycle}} + \alpha^{\text{arriv}}_{u,d,o}(k_l))\end{aligned} \tag{16}$$

and be replaced by adding a constraint to the traffic state, i.e. $0 \leq n_{u,d}(k_l) \leq C_{u,d}$. Although the improved S model leaves the oversaturated scenario out, it can also be guaranteed by the extra constraints and be convenient to design the controller based on optimal algorithm due to the reduction.

The criterion is to minimize the total time spent (TTS) of vehicles within the subnetwork, the objective function over a prediction horizon N_p^l is defined by

$$J_{\text{TTS}} = \sum_{(u,d)\in\mathcal{L}} \sum_{p=0}^{N_p^l} n_{u,d}(k_l+p) \cdot c_{\text{cycle}} \tag{17}$$

We formulate the optimization problem of subnetwork i at the lower-level as the following discrete time MPC problem:

$$\begin{aligned}&\min_{g^i(k_l)} \; J_{i,l} = J_{i,\text{TTS}}\\ &\text{s.t. link traffic flow model } (11)-(12), (14)-(16)\\ &\qquad \text{for } p = 0, \ldots, N_p^l - 1, \text{ for all } (u,d) \in \mathcal{L}_i\\ &\qquad \Phi(\mathbf{g}^i(k_l)) = 0\\ &\qquad 0 \leq \mathbf{n}_{u,d}(k_l) \leq \mathbf{C}_{u,d}\\ &\qquad \mathbf{g}^i_{\min} \leq \mathbf{g}^i(k_l) \leq \mathbf{g}^i_{\max}\end{aligned} \tag{18}$$

where $\mathcal{L}_i$ is the set of links in subnetwork i, $\mathbf{g}^i(k_l)$ is the vector containing the traffic signal green time ratios for all intersections in subnetwork i, $\Phi(\mathbf{g}^i(k_l)) = 0$ denotes that the sum of green time duration of all phases for each traffic signal is equal to its cycle time, $\mathbf{g}^i_{\min}$ and $\mathbf{g}^i_{\max}$ are the lower and upper bounds for $\mathbf{g}^i(k_l)$ respectively. In fact, the motivation of this approach is to simplify the MPC optimization problem by reducing one nonlinear equation in the dynamic control model and adding a physical constraint to the state variables.

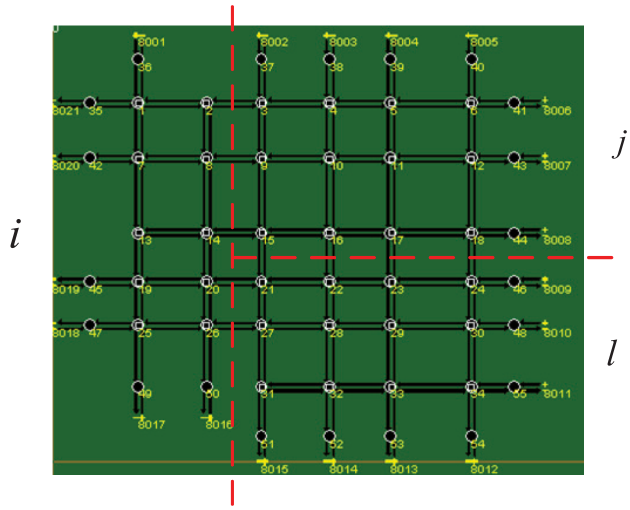

FIGURE 4. Urban traffic network modeled in CORSIM for simulation.

IV. SIMULATION AND RESULTS

A hypothetical urban traffic network has been built as the test-bed to implement the integrated hierarchical control in this section, as shown in Fig. 4, which contains 55 nodes and 154 two-way links with lengths varying from 213 to 366 meters. The traffic demands flow into the network through 21 source nodes, and 34 intersections inside the network are equipped with traffic signals. The test is carried out via a microscopic traffic simulator CORridor SIMulation (CORSIM), which allows external control strategy to operate traffic signal timing at the intersection. The loop-detectors are installed in all links to collect real-time traffic data.

The rolling-horizon optimization problem at both levels in (10) and (18) are nonlinear nonconvex programs, which can be solved by using sequential quadratic programming (SQP) in MATLAB to obtain the optimal solution. Moreover, with respect to the available global optimal solution, here we use the multi-start SQP technique discussed in [41] to prevent the optimization problem ending up in a local minimum for our case studies.

In order to establish the MFD-based traffic model at the higher-level, a heterogeneous urban traffic network has to be decomposed into several homogeneous subnetworks firstly. In our simulation, a network partition method proposed in [38] is utilized to divide the test network into three subnetworks, as shown in Fig. 4. In this approach, the whole traffic network is firstly represented by an undirected network

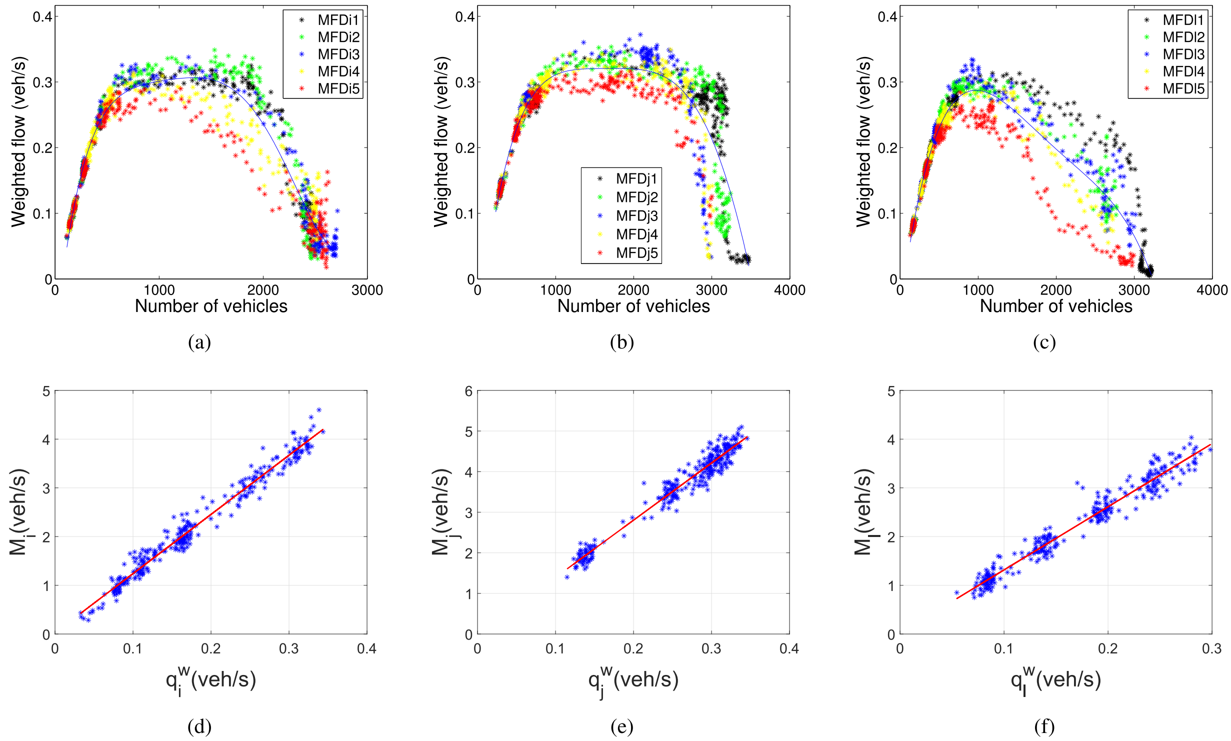

FIGURE 5. **Characteristics of MFD for each subnetwork. (a), (b) and (c) Relationship between the number of vehicles and the weighted average flow. (d), (e) and (f) Relationship between the weighted average flow and the subnetwork outflow.**

composed of nodes and edges. Secondly, it converts the topology of original network into its dual form, where each road is a node and each intersection is a link. Thirdly, a similarity function is presented to calculate the difference value of traffic state between two adjacent roads. Finally, a community detection method by optimizing the modularity, which is a criterion to evaluate the quality of division result, is utilized to decompose the whole network into several subnetworks. For more details about this approach, we would like to refer the interested reader to [38]. Since the control strategy has impact on the shape of MFD, we use the traffic data collected from five predefined fixed-time control strategies (including two strategies for undersaturated condition, one strategy for saturated condition and two strategies for oversaturated condition) to depict the shape of MFD for each subnetwork, as shown in Fig. 5(a), 5(b) and 5(c), respectively. According to the second feature of MFD, Fig. 5(d), 5(e) and 5(f) show the linear relationship between subnetwork outflow and weighted average flow. Hence, a five-order polynomial function with nonsymmetric unimodal curve can be used to establish the relationship between the number of vehicles and the subnetwork outflow in (1) via traffic data fitting, i.e., $M(k_u) = a \cdot N^5(k_u) + b \cdot N^4(k_u) + c \cdot N^3(k_u) + d \cdot N^2(k_u) + e \cdot N(k_u) + f$, where a, b, c, d, e, and f are the estimated parameters. From Fig. 5, each subnetwork with a different MFD is taken into account with the parameters $a_i = 1.0172 \times 10^{-15}$, $b_i = -7.5214 \times 10^{-12}$, $c_i = 2.0588 \times 10^{-8}$, $d_i = -2.7223 \times 10^{-5}$, $e_i = 0.0175$, $f_i = -1.1238$, $a_j = 1.2424 \times 10^{-16}$, $b_j = -1.6123 \times 10^{-12}$, $c_j = 7.2341 \times 10^{-9}$, $d_j = -1.5104 \times 10^{-5}$, $e_j = 0.0157$, $f_j = -1.3371$, $a_l = 1.2286 \times 10^{-17}$, $b_l = -5.4717 \times 10^{-13}$, $c_l = 3.8213 \times 10^{-9}$, $d_l = -1.0641 \times 10^{-5}$, $e_l = 1.1807 \times 10^{-2}$, $f_l = -0.624$, critical number of vehicles $N_{i,\text{critical}} = 1300$ veh, $N_{j,\text{critical}} = 1700$ veh, $N_{l,\text{critical}} = 1000$ veh.

TABLE 1. **Traffic demand for each source node.**

Simulation time (s)	Traffic demand flow (veh/h)	
	Scenario 1	Scenario 2
0-900	800	2000
900-1800	1000	2000
1800-2700	1200	2500
2700-3600	1500	2500
3600-4500	1500	3000
4500-5400	1000	3000

For the simulation tests, two scenarios with different traffic demands (i.e. the network input flow from external regions) are introduced to the simulator CORSIM. The first scenario is to imitate a peak and off-peak period with lightly traffic demand where the inflow first rise gradually and then descend. The second one is to produce an oversaturated traffic condition with an increasing traffic demand. For simplicity, we assume that all source nodes in the network have the same traffic demand, as illustrated in Table 1. Traffic signals for all intersections are two-phase timing plans working on a common cycle time c_{cycle} of 60 s. The total simulation time is 5400 s. Simulation control sample time at both levels is 180 s. The lower and upper bounds of the inflow ratio are chosen as $r_{i,\min} = 0.1$ and $r_{i,\max} = 0.9$. In the S model, the average vehicle length l_{veh} is set to 5 meters, the saturation flow $\mu_{u,d}$ for each link (u, d) is set to 2000 veh/h, the turning rate $\beta_{u,d,o}$ for each intersection is set to 33.33%. Bounds of the green time for all signals are $g_{\min} = 10$ s and $g_{\max} = 50$ s. Based on the analysis in [41], the prediction horizons at both levels are selected as $N_{\text{p}}^{u} = N_{\text{p}}^{l} = 7$ for the MPC scheme.

In the following, we compare network performance under four control strategies to demonstrate the effectiveness of the integrated control for complex urban traffic networks.

- Fixed-time control. The cycle time and the green time ratio for each intersection in the network have been predefined based on historical traffic data. Here, the best one of five predefined fixed-time control strategies is applied in the simulation.
- Centralized control. In this method, an MPC controller is utilized to operate the internal traffic signals within the whole network, where the S model is used as the prediction model and the TTS is considered as the objective function.
- Proposed integrated control. This approach combines the demand management MPC control strategy at the higher-level described in Section II and the traffic signals coordination MPC control strategy at the lower-level described in Section III.
- Compared hierarchical control in [30]. In this scheme, a boundary MPC control strategy based on the concept of MFD at the higher-level is applied to obtain the optimal transfer traffic flows among subnetworks, which will be sent to the lower-level controllers as reference targets. The subnetwork controller is identical to our proposed signals coordination controller except the tracking term is utilized as one of the objective functions.

Two common estimation criteria are introduced to evaluate the performances of four control approaches. The first one is TTS_{ind}, which represents the accumulated amount of TTS by all vehicles inside the traffic network since the beginning of simulation:

$$\text{TTS}_{\text{ind}} = \sum_{k=1}^{K_{\text{c}}} \sum_{(u,d)\in\mathcal{L}} T_{\text{c}} \cdot n_{u,d}(k) \tag{19}$$

where K_{c} is the control time step counts in the considered time horizon. The second one is the accumulated total delay time (TDT) from the beginning of the simulation to the end

$$\text{TDT} = \sum_{k=1}^{K_{\text{c}}} \sum_{(u,d)\in\mathcal{L}} \left(\frac{l_{u,d}}{v_{u,d}^{\text{average}}(k)} - \frac{l_{u,d}}{v_{u,d}^{\text{free}}} \right) \cdot n_{u,d}(k) \tag{20}$$

where $l_{u,d}$ is the link length, $v_{u,d}^{\text{average}}(k)$ is the vehicular average speed in link (u, d), and $v_{u,d}^{\text{free}}$=50km/h is the free-flow speed. To shed more light on the subnetwork performance under our proposed integrated MPC strategy, the weighted average flow

$$q_i^{w}(k) = \frac{\sum_{r\in\mathcal{R}_i} q_r(k) l_r}{\sum_{r\in\mathcal{R}_i} l_r} \tag{21}$$

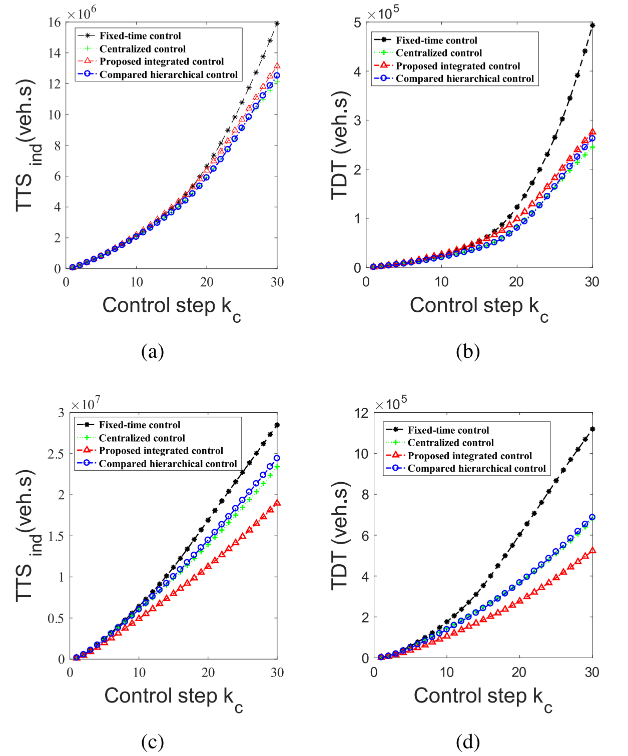

FIGURE 6. TTS_{ind} **and TDT comparison for all control approaches. (a) and (b) Scenario 1. (c) and (d) Scenario 2.**

where $\mathcal{R}_i$ is the set of links in subnetwork i and l_r is its length, $q_r(k)$ is the measured traffic flow in link r at time step k, and the number of vehicles in each subnetwork are taken into account as the criteria in the two scenarios.

Fig. 6 provides a comparison of TTS_{ind} and TDT in whole network over the simulation time for four control strategies in the two traffic scenarios. This figure demonstrates that all three MPC schemes is capable of obtaining the decreased values of TTS_{ind} and TDT. From Fig. 6(a), since the traffic network is not very congested at the beginning of the simulation period, the difference between the four control strategies is not obvious. With increased input traffic demands as time progresses, the centralized, the proposed integrated and the compared hierarchical control could obviously reduce the TTS_{ind} compared with the fixed-time control. It is also noted that the centralized control performs better than the other two hierarchical control. The difference for TTS_{ind} at the end of simulation between the centralized and the proposed integrated control is 8.26%, and the difference for TTS_{ind} between the centralized and the compared hierarchical control is 3.31%. It can be explained by the fact that the internal traffic flows within the network are well regulated and coordinated due to the presence of the lower-level controller in our approach, which prevents the network from congestion. Thus, the higher-level controller allows more input flows enter to the network during the simulation, resulting in a little more accumulated TTS_{ind} within the network. From Fig. 6(b), all three MPC control schemes can improve TDT metric

TABLE 2. TTS_{ind} **and TDT for all control strategies in the two scenarios.**

Control approach	S1				S2			
	TTS_{ind} ($\times 10^7$ veh·s)	Improvement (%)	TDT ($\times 10^5$ veh·s)	Improvement (%)	TTS_{ind} ($\times 10^7$ veh·s)	Improvement (%)	TDT ($\times 10^5$ veh·s)	Improvement (%)
Fixed-time	1.59	-	4.93	-	2.85	-	11.2	-
Centralized	1.21	23.8	2.45	50.3	2.34	17.9	6.81	39.2
Compared hierarchical	1.25	21.4	2.62	46.9	2.44	14.4	6.87	38.7
Proposed integrated	1.31	17.5	2.75	44.1	1.90	33.4	5.23	53.3

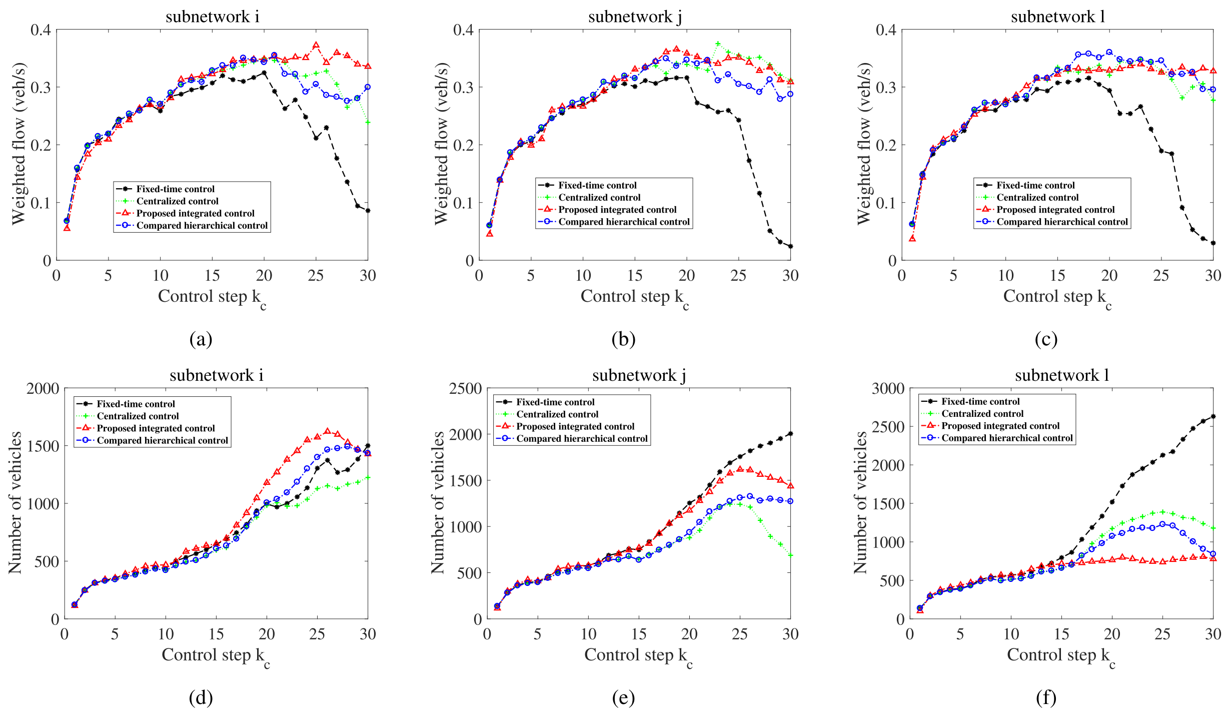

FIGURE 7. **Comparison for two performance metrics of three subnetworks under four control strategies in Scenario 1. (a), (b) and (c) Weighted average flow. (d), (e) and (f) Number of vehicles.**

compared with the fixed-time control scheme duo to their regulation ability, increasing the travel speed and decreasing the stop frequency of vehicles before they exit the network. The difference for TDT at the end of simulation between the centralized and the proposed integrated control is 12.2%, and the maximal difference between the centralized and the compared hierarchical control is 6.94%. These figures also illustrate that our integrated approach can approximate the performance of the centralized control when the network is moderately congested (as in Scenario 1).

Scenario 2 is designed to test the ability of all control strategies to against the gridlock phenomenon. From Fig. 6(c) and 6(d), the fixed-time control strategy cannot avoid severe congestion due to highly traffic demands, leading to drastic increase in accumulated TTS_{ind} and TDT for the whole network. However, compared with the centralized control and the hierarchical control, the integrated approach yields a better performance significantly in both metrics. This is reasonable since the higher-level controller will have a greatly impact on the demand management operation when the network reaches the oversaturated traffic condition. Along with a highly increasing traffic demand, the performance of the centralized and the compared hierarchical control strategies may deteriorate because of local spillback within the traffic network, whereas the integrated approach can restrict the inflows from adjacent regions so as to keep the number of vehicles of each subnetwork close to its critical value of MFD. Thus, the traffic signals coordination controllers at the lower-level are able to regulate the traffic flows within subnetworks, which can efficiently use the network capacity for improving the mobility. The two controllers work collaboratively to improve the system performance at the global network level by minimizing the probability that the whole network become congested. The detailed numerical results are given in Table 2.

To shed more light on the subnetwork performance under our proposed integrated MPC strategy, the weighted average flow and the number of vehicles in each subnetwork are taken into account as the criteria in the two scenarios. As depicted

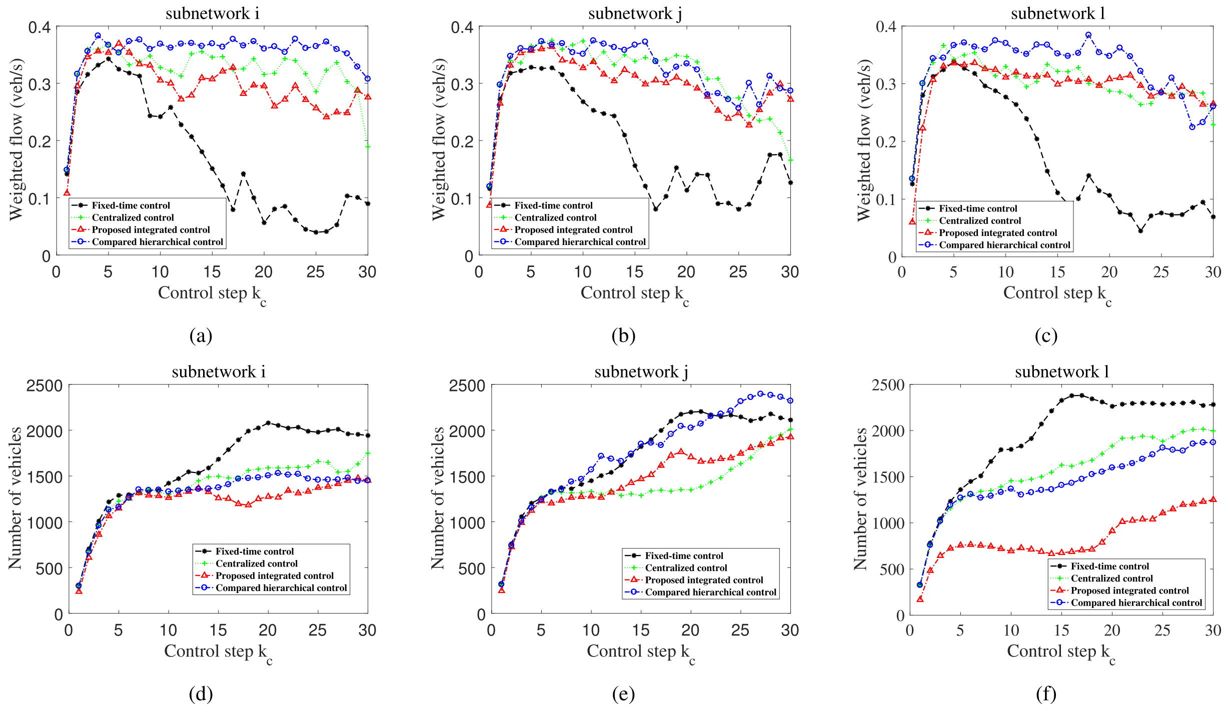

FIGURE 8. **Comparison for two performance metrics of three subnetworks under four control strategies in Scenario 2. (a), (b) and (c) Weighted average flow. (d), (e) and (f) Number of vehicles.**

in Fig. 7(a), 7(b) and 7(c) corresponding to subnetwork i, j and l respectively, all three MPC control strategies are able to increase the subnetworks flows compared with the fixed-time control in scenario 1. Fig. 7(d), 7(e) and 7(f) displays the variation of the number of vehicles over time in each subnetwork. In subnetwork j and l, our proposed approach maintain the networks $N_{j,\text{critical}} = 1700$ and $N_{l,\text{critical}} = 1000$. In subnetwork i, the number of vehicles in our approach exceeds its critical point $N_{i,\text{critical}} = 1300$ in a short duration, but the weighted average flow is kept at a relative higher level. The reason is that the aim of our higher-level controller is to maximize the internal flow within each subnetwork, attracting more inflows from external regions when the network is loaded with a moderately traffic demands. This is also can be verified in Fig. 9(a), 9(b) and 9(c), which plot the MFDs of all subnetworks in scenario 1. These figures show that our approach keeps the weighted averaged flow in subnetwork i and j at a comparatively stable state without bending the curves to the congested part (right-hand side) of MFDs, and then drives the subnetworks to recover around the critical points from the saturated condition with the decreased traffic demands in the last simulation period. In subnetwork l, the MFD in our approach is concentrated in the uncongested part (left-hand side), even without reaching the critical point. As can be observed in Fig. 9(a), 9(b) and 9(c), the other two MPC control strategies experience some lightly traffic congestion for some subnetworks.

As illustrated in Fig. 8(a), 8(b) and 8(c), compared with the fixed-time control, a remarkable improvement of weighted averaged flows for all subnetworks in scenario 2 under three MPC schemes can be observed. Our proposed approach displays a little worse performance compared with the other MPC approaches due to its lower values of weighted averaged flow. However, note also that the number of vehicles time series under our proposed control is kept below its critical value for each subnetwork, as shown in Fig. 8(d), 8(e) and 8(f). The results reveal that our proposed approach outperforms the other two MPC control strategies in managing the traffic demands among subnetworks, especially in the oversaturated traffic conditions. The reason for the lower subnetwork flow is that the function of MFD is obtained from the curve fitting method, which are not able to describe the scatter errors in the saturated and oversaturated part of MFD, leading to inefficiently usage of the network maximum flow. It may be solved by adding some stochastic terms into the MFD function in future work. The similar result is clearly seen in the MFDs for the three subnetworks in Fig. 9(d), 9(e) and 9(f).

In order to further illustrate that the integrated MPC approach is superior in distributing the number of vehicles efficiently over each subnetwork, we utilize the standard deviation (SD) of link densities to analyze the homogeneous degree within each subnetwork, which is defined as follows

$$\text{SD}_i(k_c) = \sqrt{\frac{1}{m_i} \sum_{(u,d)\in\mathcal{L}_i} \left(\frac{n_{u,d}(k_c)}{l_{u,d}} - \vartheta_i(k_c)\right)^2}$$

$$\vartheta_i(k_c) = \frac{\sum_{(u,d)\in\mathcal{L}_i} \frac{n_{u,d}(k_c)}{l_{u,d}}}{m_i} \qquad (22)$$

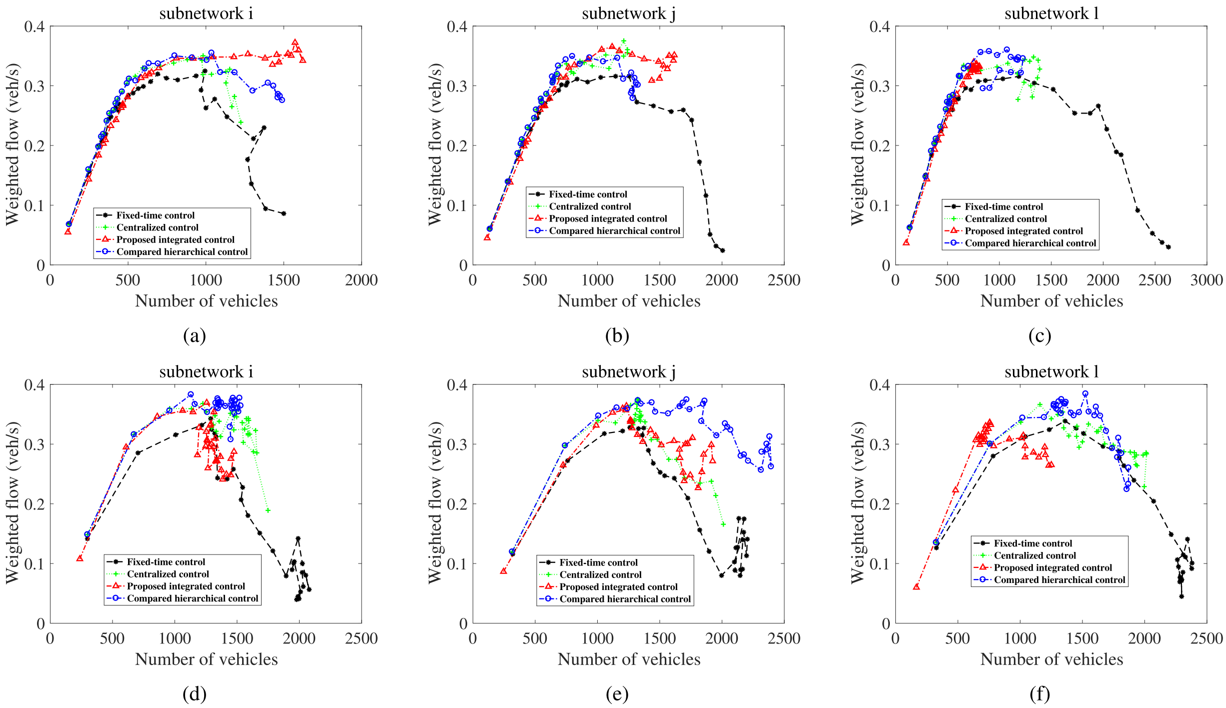

FIGURE 9. Comparison for the MFDs of three subnetworks under four control strategies. (a), (b) and (c) Scenario 1. (d), (e) and (f) Scenario 2.

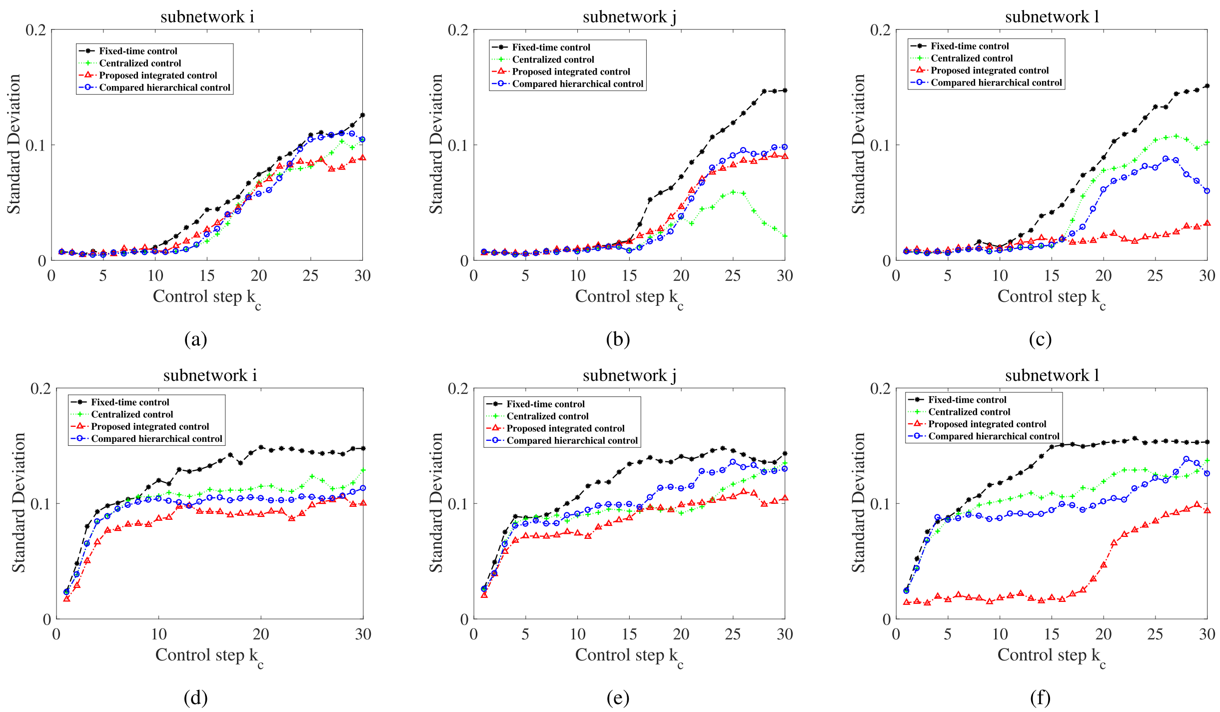

FIGURE 10. Standard deviation of link densities within three subnetworks under four control strategies. (a), (b) and (c) Scenario 1. (d), (e) and (f) Scenario 2.

where m_i is the number of links in subnetwork i, ϑ_i is the mean value of link densities in subnetwork i. Fig. 10 displays the evolution of standard deviation over time for all four control strategies. In scenario 1, our proposed approach exhibits a better performance in the standard deviation of link densities for subnetwork i and l. For subnetwork j, the performance of our approach is more close to the compared hierarchical control due to the fact that there is a quickly decrease of

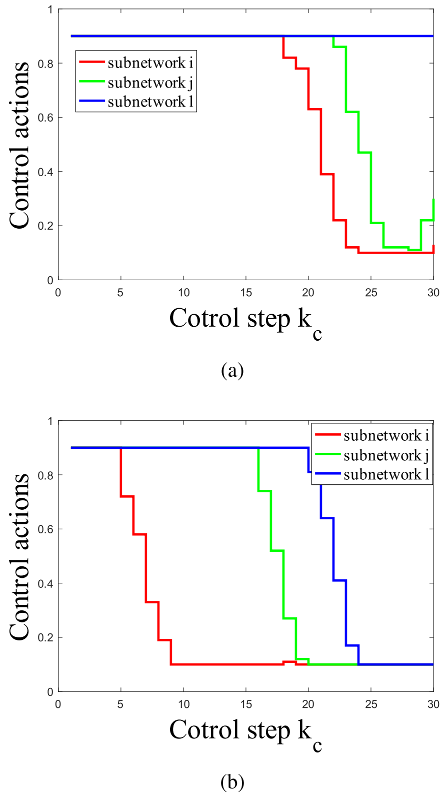

FIGURE 11. The control actions of the subnetworks. (a) Scenario 1. (b) Scenario 2.

the number of vehicles under the centralized control, resulting in the insufficiently usage of the subnetwork capacity. It also reveals the fact that the centralized control cannot coordinate the traffic flows among subnetworks effectively. In scenario 2, due to the aforementioned improvements in the weighted average flow and the number of vehicles by applying our integrated MPC control strategy, the standard deviations of link densities for all subnetworks are remarkably reduced compared with the other approaches, which means that the subnetwork homogeneity is well guaranteed and consequently the vehicular movement within the subnetwork is better smoothed.

Fig. 11 depicts the control sequences of our proposed approach at the higher level for two scenarios. The control sequences show the variation trends of number of vehicles in each subnetwork. At the very beginning of the control process, the controllers do not restrict the external traffic demands since all subnetworks are uncongested. While afterwards, as the subnetworks become more congested, the controllers attempt to prevent the traffic states falling into gridlock by changing r_i from $r_{\max}$ to $r_{\min}$ in a smooth manner.

V. CONCLUSION

An appropriate hierarchical framework brings higher efficiency and more flexibility to network-wide control of complex urban traffic networks, for the reason that it is able to distribute different goals and control strategies into different levels for solving. In this paper, on the basis heterogeneous network partition, a two-level hierarchical control scheme integrating the traffic demand management at the higher level and the traffic signals coordination controller at the lower level is proposed to control a large-scale urban traffic network. The higher-level controller based on the concept of MFD limits the input traffic flow from adjacent regions to reduce the risk of oversaturation at the network level, and the lower-level controller based on an improved link level traffic model coordinate the traffic flow within the subnetworks to smooth the vehicular movements. The rolling-horizon scheme of MPC enables the optimization problems at both level to be solved online for application in practice. They work collaboratively to guarantee a better performance of the whole network. Simulation studies show the benefits of the combined control strategy in comparison to other control strategies. A further observation is that the traffic demand management is capable of stabilizing the traffic state of subnetworks to their analytical equilibria.

In the future, we will explore how to further improve the accuracy of MFD-based traffic model and reduce the computational burden in solving the nonlinear MPC optimization problem. A potential solution is to apply a distributed scheme to coordinate the traffic signals inside the subnetworks. Some intelligent optimization algorithms should also be applied to facilitate the computational efficiency and to obtain the globally optimal solution. Possible approaches to address this problem, such as evolutionary algorithms, robust optimization algorithm and so on, will also be investigated in order to further make the proposed approach applicable in practice. Control for larger scale urban traffic networks can also be considered and investigated with the utilization of the proposed approach based on the field traffic data. In addition, more detailed simulation experiments have to be implemented to compare with other approaches presented in the literature.

REFERENCES

[1] F.-Y. Wang, "Parallel control and management for intelligent transportation systems: Concepts, architectures, and applications," *IEEE Trans. Intell. Transp. Syst.*, vol. 11, no. 3, pp. 630–638, Sep. 2010.
[2] C. Diakaki, M. Papageorgiou, and K. Aboudolas, "A multivariable regulator approach to traffic-responsive network-wide signal control," *Control Eng. Pract.*, vol. 10, no. 2, pp. 183–195, Feb. 2002.
[3] K. Aboudolas, M. Papageorgiou, A. Kouvelas, and E. Kosmatopoulos, "A rolling-horizon quadratic-programming approach to the signal control problem in large-scale congested urban road networks," *Transp. Res. C, Emerg. Technol.*, vol. 18, no. 5, pp. 680–694, Oct. 2010.
[4] Y. Zhang and Y. Zhou, "Distributed coordination control of traffic network flow using adaptive genetic algorithm based on cloud computing," *J. Netw. Comput. Appl.*, vol. 119, pp. 110–120, Oct. 2018.
[5] A. I. Delis, I. K. Nikolos, and M. Papageorgiou, "Macroscopic traffic flow modeling with adaptive cruise control: Development and numerical solution," *Comput. Math. Appl.*, vol. 70, no. 8, pp. 1921–1947, Oct. 2015.
[6] C. Ma, W. Hao, A. Wang, and H. Zhao, "Developing a coordinated signal control system for urban ring road under the vehicle-infrastructure connected environment," *IEEE Access*, vol. 6, pp. 52471–52478, Sep. 2018.

[7] L. B. de Oliveira and E. Camponogara, "Multi-agent model predictive control of signaling split in urban traffic networks," *Transp. Res. C, Emerg. Technol.*, vol. 18, no. 1, pp. 120–139, Feb. 2010.

[8] T. Tettamanti and I. Varga, "Distributed traffic control system based on model predictive control," *Periodica Polytechnica Civil Eng.*, vol. 54, no. 1, pp. 3–9, 2010.

[9] E. Camponogara and H. F. Scherer, "Distributed optimization for model predictive control of linear dynamic networks with control-input and output constraints," *IEEE Trans. Autom. Sci. Eng.*, vol. 8, no. 1, pp. 233–242, Jan. 2011.

[10] X. Zhou and Y. Lu, "Coordinate model predictive control with neighbourhood optimisation for a signal split in urban traffic networks," *IET Intell. Transport Syst.*, vol. 6, no. 4, pp. 372–379, Dec. 2012.

[11] B.-L. Ye, W. Wu, and W. Mao, "Distributed model predictive control method for optimal coordination of signal splits in urban traffic networks," *Asian J. Control*, vol. 17, no. 3, pp. 775–790, May 2015.

[12] P. Shao, L. Wang, W. Qian, Q. G. Wang, and X.-H. Yang, "A distributed traffic control strategy based on cell-transmission model," *IEEE Access*, vol. 6, pp. 10771–10778, Jan. 2018.

[13] A. Kouvelas, K. Aboudolas, M. Papageorgiou, and E. B. Kosmatopoulos, "A hybrid strategy for real-time traffic signal control of urban road networks," *IEEE Trans. Intell. Transp. Syst.*, vol. 12, no. 3, pp. 884–894, Sep. 2011.

[14] S. Lin, B. De Schutter, Y. Xi, and H. Hellendoorn, "Efficient network-wide model-based predictive control for urban traffic networks," *Transp. Res. C, Emerg. Technol.*, vol. 24, pp. 122–140, Oct. 2012.

[15] S. Lin, B. De Schutter, Y. Xi, and H. Hellendoorn, "Fast model predictive control for urban road networks via MILP," *IEEE Trans. Intell. Transp. Syst.*, vol. 12, no. 3, pp. 846–856, Sep. 2011.

[16] B.-L. Ye, W. Wu, H. Gao, Y. Lu, Q. Cao, and L. Zhu, "Stochastic model predictive control for urban traffic networks," *Appl. Sci.*, vol. 7, no. 6, p. 588, Jun. 2017.

[17] N. Geroliminis and C. F. Daganzo, "Existence of urban-scale macroscopic fundamental diagrams: Some experimental findings," *Transp. Res. B, Methodol.*, vol. 42, no. 9, pp. 759–770, Nov. 2008.

[18] C. F. Daganzo, "Urban gridlock: Macroscopic modeling and mitigation approaches," *Transp. Res. B, Methodol.*, vol. 41, no. 1, pp. 49–62, 2007.

[19] M. Keyvan-Ekbatani, A. Kouvelas, I. Papamichail, and M. Papageorgiou, "Exploiting the fundamental diagram of urban networks for feedback-based gating," *Transp. Res. B, Methodol.*, vol. 46, no. 10, pp. 1393–1403, Dec. 2012.

[20] J. Haddad and A. Shraiber, "Robust perimeter control design for an urban region," *Transp. Res. B, Methodol.*, vol. 68, pp. 315–332, Oct. 2014.

[21] A. Kouvelas, M. Saeedmanesh, and N. Geroliminis, "Enhancing model-based feedback perimeter control with data-driven online adaptive optimization," *Transp. Res. B, Methodol.*, vol. 96, pp. 26–45, Feb. 2017.

[22] N. Geroliminis, J. Haddad, and M. Ramezani, "Optimal perimeter control for two urban regions with macroscopic fundamental diagrams: A model predictive approach," *IEEE Trans. Intell. Transp. Syst.*, vol. 14, no. 1, pp. 348–359, Mar. 2013.

[23] K. Aboudolas and N. Geroliminis, "Perimeter and boundary flow control in multi-reservoir heterogeneous networks," *Transp. Res. B, Methodol.*, vol. 55, pp. 265–281, Sep. 2013.

[24] M. Keyvan-Ekbatani, M. Yildirimoglu, N. Geroliminis, and M. Papageorgiou, "Multiple concentric gating traffic control in large-scale urban networks," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 4, pp. 2141–2154, Aug. 2015.

[25] J. Haddad, M. Ramezani, and N. Geroliminis, "Cooperative traffic control of a mixed network with two urban regions and a freeway," *Transp. Res. B, Methodol.*, vol. 54, no. 8, pp. 17–36, Aug. 2013.

[26] M. Hajiahmadi, J. Haddad, B. De Schutter, and N. Geroliminis, "Optimal hybrid perimeter and switching plans control for urban traffic networks," *IEEE Trans. Control Syst. Technol.*, vol. 23, no. 2, pp. 464–478, Mar. 2015.

[27] N. Zheng and N. Geroliminis, "On the distribution of urban road space for multimodal congested networks," *Transp. Res. B, Methodol.*, vol. 57, pp. 326–341, Nov. 2013.

[28] I. I. Sirmatel and N. Geroliminis, "Economic model predictive control of large-scale urban road networks via perimeter control and regional route guidance," *IEEE Trans. Intell. Transp. Syst.*, vol. 19, no. 4, pp. 1112–1121, Apr. 2018.

[29] J. Haddad and B. Mirkin, "Coordinated distributed adaptive perimeter control for large-scale urban road networks," *Transp. Res. C, Emerg. Technol.*, vol. 77, pp. 495–515, Apr. 2017.

[30] Z. Zhou, B. De Schutter, S. Lin, and Y. Xi, "Two-level hierarchical model-based predictive control for large-scale urban traffic networks," *IEEE Trans. Control Syst. Technol.*, vol. 25, no. 2, pp. 496–508, Mar. 2017.

[31] Z. Zhou, S. Lin, Y. Xi, D. Li, and J. Zhang, "A hierarchical urban network control with integration of demand balance and traffic signal coordination," *IFAC-PapersOnLine*, vol. 49, no. 3, pp. 31–36, 2016.

[32] D. Q. Mayne and J. B. Rawlings, *Model Predictive Control Theory and Design*. Madison, WI, USA: Nob Hill Publishing, 2009.

[33] Y. Zhou and X. Tao, "Robust safety monitoring and synergistic operation planning between time- and energy-efficient movements of high-speed trains based on MPC," *IEEE Access*, vol. 6, pp. 17377–17390, Mar. 2018.

[34] F. Zhang, Y. Du, W. Liu, and P. Li, "Model predictive power control for cooperative vehicle safety systems," *IEEE Access*, vol. 6, pp. 4797–4810, Jan. 2018.

[35] Z. Li, Q. Cao, Y. Zhao, and R. Zhuo, "Signal cooperative control with traffic supply and demand on a single intersection," *IEEE Access*, vol. 6, pp. 54407–54416, Sep. 2018.

[36] N. Geroliminis and J. Sun, "Properties of a well-defined macroscopic fundamental diagram for urban traffic," *Transp. Res. B, Methodol.*, vol. 45, no. 3, pp. 605–617, Mar. 2011.

[37] Y. Ji and N. Geroliminis, "On the spatial partitioning of urban transportation networks," *Transp. Res. B, Methodol.*, vol. 46, no. 10, pp. 1639–1656, Dec. 2012.

[38] Z. Zhou, S. Lin, and Y. Xi, "A dynamic network partition method for heterogenous urban traffic networks," in *Proc. 15th Int. IEEE Conf. Intell. Transp. Syst.*, Anchorage, AK, USA, Sep. 2012, pp. 820–825.

[39] M. Ramezani, N. de Lamberterie, A. Skabardonis, and N. Geroliminis, "A link partitioning approach for real-time control of queue spillbacks on congested arterials," *Transportmetrica B, Transport Dyn.*, vol. 5, no. 2, pp. 177–190, 2017.

[40] S. Lin, Q.-J. Kong, and Q. Huang, "A simulation analysis on the existence of network traffic flow equilibria," *IEEE Trans. Intell. Transp. Syst.*, vol. 15, no. 4, pp. 1706–1713, Aug. 2014.

[41] Z. Zhou, B. D. Schutter, S. Lin, and Y. Xi, "Multi-agent model-based predictive control for large-scale urban traffic networks using a serial scheme," *IET Control Theory Appl.*, vol. 9, no. 3, pp. 475–484, 2015.

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