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Model-Free Adaptive Predictive Control for an Urban Road Traffic Network via Perimeter Control

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ABSTRACT This paper proposes a novel model-free adaptive control (MFAC) strategy for urban road traffic network via perimeter control based on dynamic linearization technique and predictive control. The accurate traffic flow model of the urban road network is replaced by equivalent data model. Based on the idea of predictive control, the current control action is obtained by solving online, at each sampling coordinate, a finite horizon closed-loop optimal control problem. The robustness of the MFAC strategy to time-varying desired vehicle accumulation, random traffic demand and macroscopic fundamental diagram (MFD) model uncertainty is verified through simulation results.

INDEX TERMS MFAC, model predictive control (MPC), MFD, perimeter control, urban road traffic network.

I. INTRODUCTION

In the field of traffic engineering, urban road traffic network has become increasingly important. The main reason is the rapid development of transportation network infrastructure and demand in metropolitan areas around the world.

Modelling of transportation networks based on MFD was initially proposed by Godfrey in [1], and the existence was provided later by rigorous theory from Daganzo [3]. MFD provides aggregate relationships among traffic variables at urban networks, i.e. the MFD can respectively link between network vehicle density (veh/km) or accumulation (veh) and network space-mean flow and trip completion flow (veh/hr). The MFD aims at developing aggregate MFD-based models of the traffic flow dynamics for large-scale urban road traffic networks by reducing the modelling complexity.

MFD enables the design of elegant control strategies while improving mobility and decreasing delays in large road networks. They were found to firstly describe the dynamics of a congested urban road traffic network in Yokohama (Geroliminis and Daganzo in [2]). Adopting the concept of MFD to model and traffic flow control on large-scale urban road, traffic networks have been investigated extensively in the past few years, such as [5], [6], [24], [25].

The concept of MFD is also the basis of perimeter control strategies. In perimeter control, MFD is used to manipulate the transfer flows along the perimeter of an urban road region. Different control approaches have been implemented to solve the perimeter control problems, such as feedback control approach and optimal control. The classical feedback control approach was adopted in [5], [6], where a Proportional-Integral (PI) perimeter controller was designed for an urban road region in [5], while in [6] a multivariable feedback regulator for multiple regions was appeared. Recently, an optimal perimeter controllerin [7] for a two-region urban city is formulated by exploiting the notion of MFD.

Model predictive heuristic control (MPHC) [8], dynamic matrix predictive control [22], and generalized predictive control (GPC) [9] are representative algorithms in MPC field. MPC methods have achieved great success in practical applications, especially in traffic network control [10]–[12]. In [10], mixed-integer linear programming (MILP) was proposed to increase the online feasibility of the proposed MPC method. According to the results in [10], efficient network-wide MPC-based control methods are investigated [11]. In [12], a decentralized multi-agent MPC is proposed for decoupled urban road traffic network. Although MPC has

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many advantages, such as high control performance and robustness to uncertainties and/or disturbances, the plant model or its structure is still required to be known for controller design, and the accuracy of the model will directly affect the control performance. Practically, an accurate traffic flow model of certain urban road network is difficult to establish and may be sensitive to some parameters of the traffic network, including turning ratios, exit rates and saturation flows. As a result, it is desirable to design a model-free or data-driven control strategy for phase splits in urban road traffic network.

Neural adaptive control [15], [16] and fuzzy adaptive control [17] can realize adaptive control for nonlinear systems without the need of an accurate model dynamics. While either a comprehensive understanding of the controlled system in order to establish fuzzy rules or massive operation data of the system to train neural networks is needed. Generally speaking, the controller design depends on fuzzy rules or neural network model, thus, the fundamental problems of model-based control still exist there.

MFAC [13], [14] methodology proposed by Hou is designed and analyzed based on the dynamic linearization technique (DLT) for discrete-time nonlinear systems. These theoretical analysis and extensive field applications show their effectiveness and applicability to unknown discrete-time nonlinear systems. In reference [23], a model-free adaptive predictive controller is lifted for phase splits of the urban road traffic network. MFAC, which only uses the input and output data of closed-loop systems relaxes the requirement of predictive control accuracy.

This paper proposed a model-free adaptive control approach for urban road traffic network via perimeter control. The predictive data model from dynamic linearization is used to improve the control performance, and the effectiveness of this control strategy is verified by simulation comparison with the traditional PID controller using Matlab.

Starting with the perimeter control of urban road traffic network of Beijing, a simulation model is built by Vissim simulation platform, based on the MFD obtained in advance. A model-free adaptive control algorithm for an urban road traffic network is designed via perimeter control. This paper considers the difference between the control algorithm in theory and practical application to better play the role of control and further achieve the good performance on traffic congestion.

II. PROBLEM FORMUATION

In this paper, a heterogeneous traffic network that can be partitioned into two homogeneous regions is considered. The traffic network for a two-region system is schematically shown in Fig 1. The traffic model based on vehicle conservation equation [18] can be described using equation (1)-(3), as shown at the bottom of this page.

$q_{11}(t)(veh/s)$ is internal traffic demand for region 1. $q_{12}(t)(veh/s)$ is vehicle flow demand from region 1 to region 2. $q_{21}(t)(veh/s)$ is vehicle flow demand from region 2 to region 1. $n_{11}(t)(veh)$ is the cumulative number of vehicles on the road network destined for region 1 in region 1. $n_{12}(t)(veh)$ is the cumulative number of vehicles on the road network destined for region 1 in region 2. $n_1(t)(veh)$is cumulative number of vehicles for region 1 road network. where $n_1(t) = n_{11}(t) + n_{12}(t)$.

$G_1(n_1(t))(veh/s)$ represents the total number of vehicles in region 1 at t instant. The control input satisfy $0 \leq u(t) \leq 1$, which is used to adjust the flow ratio from region 1 to region 2 or from region 2 to region 1 at the regional boundary.

The control task of this paper is to design an appropriate control algorithm to update the control input $u(t)$, so as to the cumulative number of vehicles in region 1 can reach the desired number of vehicles $n_{1,ss}$.

III. DESIGN OF MODEL-FREE ADAPTIVE PREDICTIVE BOUNDARY CONTROLLER

Define $\alpha(t) = n_{11}(t)/n_1(t)$, combine (1) and (2), we obtain

$$\frac{dn_1(t)}{dt} = q_{11}(t) + q_{12}(t) + (1 - u(t)) \cdot q_{21}(t) - \alpha(t) \cdot G_1(n_1(t)) - (1 - \alpha(t)) \cdot u(t) \cdot G_1(n_1(t)) \tag{4}$$

Set sampling time as T, discrete (4), we can obtain

$$\begin{aligned} n_1(k+1) &= n_1(k) + T\,(q_{11}(k) + q_{12}(k) + (1 - u(k)) \cdot q_{21}(k)) \\ &\quad - T\,(\alpha(k) \cdot G_1(n_1(k)) - (1 - \alpha(k)) \cdot u(k) G_1(n_1(k))) \end{aligned} \tag{5}$$

System (5) has the following two properties.

Properties 1: Except for limited time instants, the partial derivative of $n_1(k+1)$ with respect to variable $u(k)$ is continuous.

Properties 2: Except for limited time instants, the system satisfies the generalized Lipschitz condition, namely, for any $k_1 \neq k_2, k_1, k_2 \geq 0$, (6) can be established.

$$|n_1(k_1 + 1) - n_1(k_2 + 1)| \leq b|u(k_1) - u(k_2)| \tag{6}$$

where $b > 0$ is a constant.

It's obviously that the partial derivative of (5) with respect to variable $u(k)$ is continuous, thus the correctness of property 1 is verified. In the actual traffic network, the number of

$$\frac{dn_{11}(t)}{dt} = q_{11}(t) + (1 - u(t)) \cdot q_{21}(t) - \frac{n_{11}(t)}{n_1(t)} \cdot G_1(n_1(t)) \tag{1}$$

$$\frac{dn_{12}(t)}{dt} = q_{12}(t) - \frac{n_{12}(t)}{n_1(t)} \cdot G_1(n_1(t)) \cdot u(t) \tag{2}$$

$$n_1(t) = n_{11}(t) + n_{12}(t) \tag{3}$$

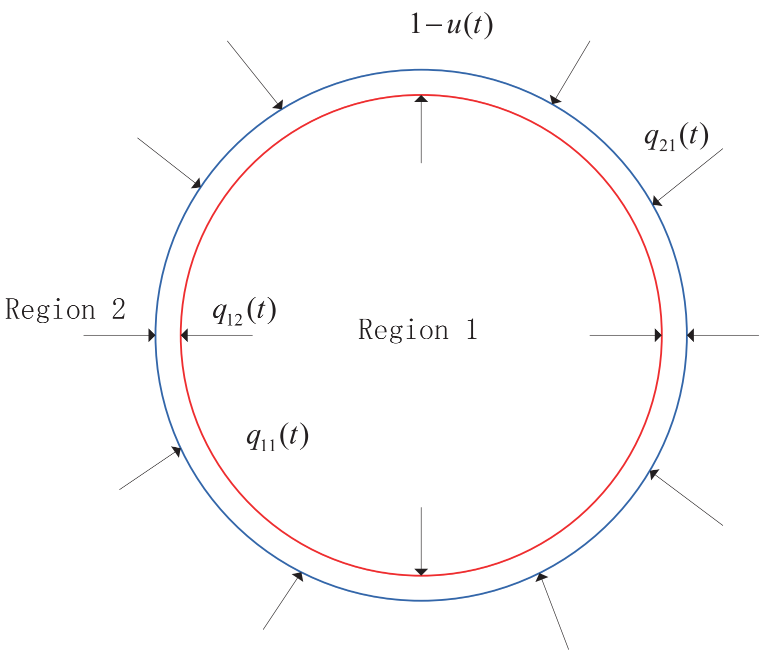


FIGURE 1. Two-region MFDs system.

vehicles will not increase indefinitely, thus, generalized Lipschitz condition can be satisfied for system (5), property 2 is verified.

According to [14], for a class of nonlinear systems which satisfying properties 1 and 2, when $|\Delta u(k)| \neq 0$, there must exist a time-varying parameter $\phi_c(k) \in R$ called pseudo-partial derivative (PPD). The non-linear system can be transformed into the following compact form dynamic linearization (CFDL) model (7).

$$n_1(k+1) = n_1(k) + \phi_c(k) \cdot \Delta u(k) \tag{7}$$

and $\phi_c(k)$ is bounded and nonsingular at any time instant k.

Remark 1: $\phi_c(k)$ is related to the system inputs and outputs. However, $\phi_c(k)$ is a differential signal in some sense and bounded for any time instant k. So we can regard $\phi_c(k)$ as a slowly time-varying parameter.

According to (7), N-step-ahead prediction equations are given as formula (8):

And let

$$\begin{aligned} Y_N(k+1) &= [n_1(k+1), \cdots, n_1(k+N)]^T \\ \Delta U_N(k) &= [\Delta u_N(k), \cdots, \Delta u_N(k+N-1)]^T \\ E_k &= [1, \cdots, 1]^T \end{aligned}$$

where $Y_N(k+1)$ denotes the N-step-ahead prediction vector of the system output. $\Delta U_N(k)$ is the control input increment vector, and N_u is the control input horizon.

Then Formula (8), as shown at the bottom of this page, can be rewritten in a compact form:

$$Y_N(k+1) = E(k)n_1(k) + A(k)\Delta U_N(k) \tag{9}$$

The definition of matrix A can be found in formula (10).

If $\Delta u(k+j-1) = 0, j > N_u$, then prediction equation (9) can be formulated as (11), as shown at the bottom of the next page,

$$Y_N(k+1) = E(k)n_1(k) + A_1(k)\Delta U_{N_u}(k) \tag{10}$$

where

$$A_1(k) = \begin{bmatrix} \phi_c(k) & 0 & 0 & 0 \\ \phi_c(k) & \phi_c(k+1) & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \phi_c(k) & \phi_c(k+1) & \cdots & \phi_c(k+N_u-1) \\ \vdots & \vdots & \cdots & \vdots \\ \phi_c(k) & \phi_c(k+1) & \cdots & \phi_c(k+N_u-1) \end{bmatrix}_{N \times N_u}$$

and $\Delta U_{N_u}(k) = [\Delta u_(k), \cdots, \Delta u_(k+N_u-1)]^T$

$$\begin{cases} n_1(k+1) = n_1(k) + \phi_c(k) \cdot \Delta u(k) \\ n_1(k+2) = n_1(k+1) + \phi_c(k+1) \cdot \Delta u(k+1) \\ \qquad = n_1(k) + \phi_c(k) \cdot \Delta u(k) + \phi_c(k+1) \cdot \Delta u(k+1) \\ \qquad \vdots \\ n_1(k+N) = n_1(k+N-1) + \phi_c(k+N-1) \cdot \Delta u(k+N-1) \\ \qquad = n_1(k+N-2) + \phi_c(k+N-2) \cdot \Delta u(k+N-2) + \phi_c(k+N-1) \cdot \Delta u(k+N-1) \\ \qquad \vdots \\ \qquad = n_1(k) + \phi_c(k) \cdot \Delta u(k) + \cdots + \phi_c(k+N-1) \cdot \Delta u(k+N-1) \end{cases} \tag{8}$$

A. CONTROLLER ALGORITHM

The following control input criterion function (12) is considered

$$J=\sum_{i=1}^{N}\left(n_1(k+i)-n_1{}^*(k+i)\right)^2+\lambda\sum_{j=0}^{N_u-1}\Delta u^2(k+j) \quad (12)$$

where $\lambda > 0$ is a weighting factor, and $n_1{}^*(k+i)$ is the desired output of the system at $k+i$ instant, $i = 1, 2 \cdots N$.

Let $Y_N^*(k+1) = [n_1^*(k+1), \cdots, n_1^*(k+N)]^T$, then the cost function (12) becomes

$$J = [Y_N^*(k+1) - Y_N(k+1)]^T[Y_N^*(k+1) - Y_N(k+1)] + \lambda \Delta U_{N_u}^T \Delta U_{N_u} \quad (13)$$

To obtain the controller, differentiating the performance index J with respect to $\Delta U_{N_u}(k)$, setting the derivative equals to zero yield the control law:

$$\Delta U_{N_u}(k) = \left[A_1^T(k)A_1(k) + \lambda I\right]^{-1} A_1^T(k) \times \left[Y_N^*(k+1) - E(k)n_1(k)\right] \quad (14)$$

Thus, the control input at current time k is obtained according to the receding horizon principle as follows:

$$u(k) = u(k-1) + g^T \cdot \Delta U_{N_u}(k) \quad (15)$$

where $g = [1, 0, \cdots, 0]^T$.

When $N_u = 1$, Equation (15) becomes

$$u(k) = u(k-1) + \frac{1}{\phi_c^2(k) + \lambda\backslash N}\frac{1}{N} \cdot [\phi_c(k)\sum_{i}^{N}(n_1^*(k+i) - n_1(k))] \quad (16)$$

B. PPD ESTIMATION ALGORITHM AND PREDICTION ALGORITHM

Since $A_1(k)$ in (15) contains unknown PPD parameters $\phi_c(k), \phi_c(k+1), \cdots, \phi_c(k+N_u-1)$, some time-varying parameter estimation or prediction algorithm should be developed when it is used in applications. Theoretically speaking, any estimation algorithm for time-varying parameters can be applied to PPD parameter estimation, but we still use the modified projection algorithm to estimate $\phi_c(k)$ here in order to facilitate the theoretical analysis for the control system, that is,

$$\hat{\phi}_c(k) = \hat{\phi}_c(k-1) + \frac{\eta \Delta u(k-1)}{\mu + \Delta u(k-1)^2} \cdot [\Delta n_1(k) - \hat{\phi}_c(k-1)\Delta u(k-1)] \quad (17)$$

where $\mu > 0$ is a weighting factor, and $0 < \eta < 1$ is a step size factor.

Since $\phi_c(k+1), \cdots, \phi_c(k+N_u-1)$ cannot be directly calculated from the I/O data till sample time k, they need be predicted according to the past estimated sequence $\hat{\phi}_c(1), \cdots, \hat{\phi}_c(k)$. In this paper, the multilevel hierarchical forecasting method [13] is applied here to predict unknown parameters $\phi_c(k+1), \cdots, \phi_c(k+N_u-1)$.

Assume that the estimated values $\phi_c(1), \cdots, \phi_c(k)$ have been calculated by (17) at time k. Using these estimated values, an auto regressive (AR) model for prediction is constructed as follows:

$$\hat{\phi}_c(k+1) = \theta_1(k)\hat{\phi}_c(k) + \theta_2(k)\hat{\phi}_c(k-1) + \cdots + \theta_{n_p}(k)\hat{\phi}_c(k-n_p+1) \quad (18)$$

where $\theta_i, i = 1, \cdots, n_p$ is the coefficient and n_p is the fixed model order, which is usually set to $2-7$ as recommended.

Using (18), the prediction equation becomes,

$$\hat{\phi}_c(k+j) = \theta_1(k)\hat{\phi}_c(k+j-1) + \theta_2(k)\hat{\phi}_c(k+j-2) + \cdots + \theta_{n_p}(k)\hat{\phi}_c(k+j-n_p) \quad (19)$$

where $j = 1, \cdots, N_u - 1$.

Let $\boldsymbol{\theta}(k) = [\theta_1(k), \cdots, \theta_{n_p}(k)]^T$, it is determined by the following equation:

$$\boldsymbol{\theta}(k) = \boldsymbol{\theta}(k-1) + \frac{\hat{\boldsymbol{\phi}}(k-1)}{\delta + \|\hat{\boldsymbol{\phi}}(k-1)\|^2} \cdot [\hat{\phi}_c(k) - \hat{\boldsymbol{\phi}}^T(k-1)\boldsymbol{\theta}(k-1)] \quad (20)$$

where $\hat{\boldsymbol{\phi}}(k-1) = [\hat{\phi}_c(k), \cdots, \hat{\phi}_c(k-n_p)]$, and $\delta \in (0, 1]$ is a positive constant.

C. CONTROL SCHEME

Integrating control algorithm (15), parameter estimation algorithm (17), and the prediction algorithm (19) and (20), model-free adaptive predictive control (MFAPC) scheme is

$$A(K) = \begin{bmatrix} \phi_c(k) & 0 & 0 & 0 & 0 & 0 \\ \phi_c(k) & \phi_c(k+1) & 0 & 0 & & \\ \vdots & \vdots & \ddots & \vdots & & \vdots \\ \phi_c(k) & \cdots & & \phi_c(k+N_u-1) & & \\ \vdots & & & \vdots & \ddots & 0 \\ \phi_c(k) & \phi_c(k+1) & \cdots & \phi_c(k+N_u-1) & \cdots & \phi_c(k+N-1) \end{bmatrix}_{N\times N} \quad (11)$$

designed as follows:

$$\hat{\phi}_c(k) = \hat{\phi}_c(k-1) + \frac{\eta \Delta u(k-1)}{\mu + \Delta u(k-1)^2} \cdot [\Delta n_1(k) - \hat{\phi}_c(k-1)\Delta u(k-1)] \quad (21)$$

$$\hat{\phi}_c(k) = \hat{\phi}_c(1) \quad if \quad |\hat{\phi}_c(k)| \le \varepsilon \quad or \quad |\Delta u(k-1)| \le \varepsilon \quad or \quad sign(\hat{\phi}_c(k)) \ne sign(\hat{\phi}_c(1)) \quad (22)$$

$$\boldsymbol{\theta}(k) = \boldsymbol{\theta}(k-1) + \frac{\hat{\boldsymbol{\phi}}(k-1)}{\delta + \|\hat{\boldsymbol{\phi}}(k-1)\|^2} \cdot [\hat{\phi}_c(k) - \hat{\boldsymbol{\phi}}^T(k-1)\boldsymbol{\theta}(k-1)] \quad (23)$$

$$\boldsymbol{\theta}(k) = \boldsymbol{\theta}(1), if \ \|\boldsymbol{\theta}(k)\| \ge M, \quad (24)$$

$$\hat{\phi}_c(k+j) = \theta_1(k)\hat{\phi}_c(k+j-1) + \theta_2(k)\hat{\phi}_c(k+j-2) + \cdots + \theta_{n_p}(k)\hat{\phi}_c(k+j-n_p) \quad j = 1, 2, \cdots, N_u - 1 \quad (25)$$

$$\hat{\phi}_c(k+j) = \hat{\phi}_c(1), \quad if\, |\hat{\phi}_c(k+j)| < \varepsilon \quad or \quad sign(\hat{\phi}_c(k+j)) \ne sign(\hat{\phi}_c(1)), \quad j = 1, 2, \cdots, N_u - 1 \quad (26)$$

$$\Delta U_{N_u}(k) = \left[A_1^T(k)A_1(k) + \lambda I\right]^{-1} A_1^T(k) \times \left[Y_N^*(k+1) - E(k)n_1(k)\right] \quad (27)$$

$$u(k) = u(k-1) + g^T \cdot \Delta U_{N_u}(k) \quad (28)$$

where $\varepsilon, \lambda, \mu$ and M are positive constants, η *and* $\delta \in (0, 1]$, $\hat{A}_1(k)$ and $\hat{\phi}_c(k+j)$ are the estimated values of $A_1(k)$ and $\phi_c(k+j)$ respectively.

The stability and convergence can be seen the proof of Theorem 6.1 in [14].

IV. SIMULATION STUDY

A. SIMULATION SETUP

In this section, an isolated junction with 4 phases is simulated on Matlab platform to show the effectiveness of the proposed scheme for phase splits.

The MFD is well defined, that is, there is no uncertainty. The parameters of the selected regional macroscopic fundamental diagram (MFD) are set as (29), and the shape of the MFD is schematically shown in Fig.2. For controller parameter tuning, the sampling period adopted is 1 second and the simulation time is 10800 seconds.

$$\begin{aligned} G_{1(n_1)} &= (-0.02331 n_1{}^2 + 29.3706 n_1)/3600 \\ n_{1,cr} &= 630(veh) \\ G_1(n_{1,cr}) &= 2.57(veh/s) \\ n_{1,jam} &= 1260(veh) \\ \alpha\,(0) &= 0.2 \end{aligned} \quad (29)$$

Two scenario was considered, the initial accumulations $n_1(0)$ is set to be 200 in initial nocongested network and $n_1(0) = 1000$ in initial congested network.

The parameters of MFAPC scheme are $n = 3, n_u = 1, \varepsilon = 10^{-5}, \delta = 1, \eta = 1$. The initial value of PJM is set to be.

Flow on the boundary is also accurate, that is, there is no measurement noise. Flow demand is shown in Table 1.

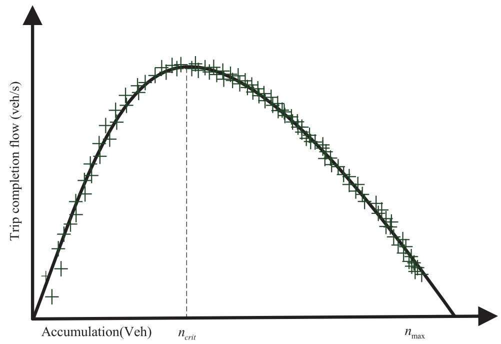
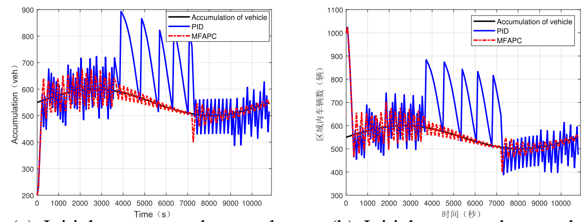


FIGURE 2. The shape of the MFD.

TABLE 1. Constant traffic demand.

Time (Hour)	Flow (Vehicle /S)
6:00 to 6:30	$q_{11} = 0.2, q_{12} = 0.2, q_{21} = 2.0$
6:30 to 7:00	$q_{11} = 0.2, q_{12} = 0.4, q_{21} = 3.0$
7:00 to 8:00	$q_{11} = 1.0, q_{12} = 1.0, q_{21} = 5.0$
8:00 to 8:30	$q_{11} = 0.2, q_{12} = 0.1, q_{21} = 2.0$
8:30 to 9:00	$q_{11} = 0.2, q_{12} = 0.2, q_{21} = 2.0$



(a) Initial nocongested network (b) Initial congested network

FIGURE 3. Control performance with time-varying desired vehicle accumulation.

B. SIMULATION RESULT

In order to demonstrate the advantages of the model-free adaptive predictive boundary control algorithm, traditional PID boundary control algorithm is involved under different scenarios, including time-varying desired accumulation vehicle, random traffic demand and MFD model uncertainty.

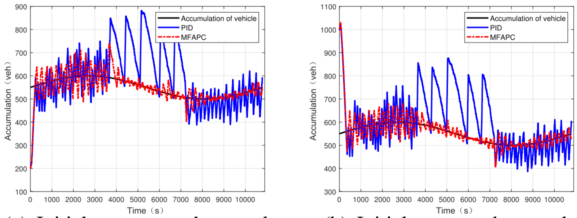
1) TIME-VARYING DESIRED VEHICLE ACCUMULATION

On the one hand, it is difficult to determine an accurate desired vehicle accumulation due to the complexity of traffic network. On the other hand, the universality of the algorithm require the tracking task should be complex and changeable. And a time-varying desired vehicle accumulation could better react the real traffic situation than a time invariant desired vehicle accumulation. In this scenario, $n_{1,ss} = 550 + 50 * sin(k * pi/5400)$.

The control performances under the method of PID and MFAPC are shown in Fig. 3. The results show that both PID algorithm and the proposed model-free adaptive predictive boundary control algorithm (MFAPPC) can realize desired vehicle accumulation tracking under complicated scenes. When the morning peak arriving at 7 : 30, it begins to appear a very large tracking fluctuation using PID method. While the proposed method could realize almost perfect tracking, which achieves a better performance than PID.

TABLE 2. Time-varying traffic demand.

Time (Hour)	Flow (Vehicle /S)
6:00 to 6:30	$q_{11} = [0.16, 0.24], q_{12} = [0.16, 0.24], q_{21} = [1.6, 2.4]$
6:30 to 7:00	$q_{11} = [0.16, 0.24], q_{12} = [0.32, 0.48], q_{21} = [2.4, 3.6]$
7:00 to 8:00	$q_{11} = [0.80, 1.20], q_{12} = [0.80, 1.20], q_{21} = [4.0, 6.0]$
8:00 to 8:30	$q_{11} = [0.16, 0.24], q_{12} = [0.08, 0.12], q_{21} = [1.6, 2.4]$
8:30 to 9:00	$q_{11} = [0.16, 0.24], q_{12} = [0.16, 0.24], q_{21} = [1.6, 2.4]$



(a) Initial nocongested network (b) Initial congested network

FIGURE 4. Control performance under random traffic demand.

2) RANDOM TRAFFIC DEMAND

Traffic demand is also a uncertainty factor in the actual traffic systems. On the one hand, the detection ability of vehicle detector is limited, it can't give the accurate vehicle number at each sampling time. on the other hand, the drivers' route choice is not entirely fixed due to their temporary behavior, thus it is difficult to count the exact traffic demand.

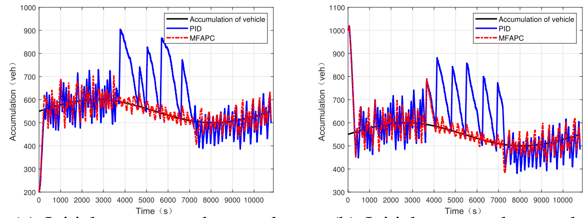
Comparing to the fixed traffic demand is table (1), the random varying traffic demand is used in table (2) to simulate the traffic demand.

The tracking performance of the two boundary control algorithms in the initial nocongested network and congested road network is studied. The variation of vehicle cumulative number in the road network is shown in Fig. (4). It can be seen that model-free adaptive predictive boundary control algorithm still could achieve a good tracking performance under more complex traffic demand, which increases the application possibility of the proposed in practice traffic road network. It is precisely because model-free adaptive predictive boundary control algorithm synthesizes the advantages of the model-free adaptive control and predictive control. Accurate model is not needed in model-free adaptive control. While future steps could be predicted using predictive control under many uncertainties or time-varying variables.

3) MFD MODEL WITH UNCERTAINTY

In previous simulation scenarios, MFD model is considered well defined. In practices, there exists errors in the process of data measurement, collection, handling and fitting. And these errors could lead to the uncertainty of the MFD model. The vehicle cumulative number in the road network is shown in Fig. (5).

Compared with the simulation scenario 1, 2 and 3, the control effect is slightly reduced in this scenario, while the tracking error is also within acceptable range. It also can been seen that the uncertainty of the MFD model is an important factor for perimeter control for urban traffic network.



(a) Initial nocongested network (b) Initial congested network

FIGURE 5. Control performance with MFD uncertainty.

C. SUMMARY OF SIMULATION

In the simulation of this chapter, the tracking effects of model-free adaptive predictive boundary control and traditional PID control are observed and analyzed under there simulation scenarios. It is not difficult to see that the proposed model-free adaptive predictive perimeter control algorithm based on MFD has good tracking performance and strong robustness. Feasibility and control performance of the two control algorithms were compared using MATLAB software.

V. CONCLUSION

In this paper, a MFAC strategy is developed for urban road traffic network with perimeter control. It is different from the studies based on the known traffic model that the dynamic model of the MFD considered here is unknown except for input/output data. Utilizing the dynamic linearization technique and the principle of predictive control, the proposed control scheme is obtained online by minimizing an cost function in prediction horizon. The simulation studies verify the effectiveness of the proposed operation strategy by time-varying desired vehicle accumulation, random traffic demand and MFD model uncertainty. It can be used in urban road traffic systems to improve traffic response.

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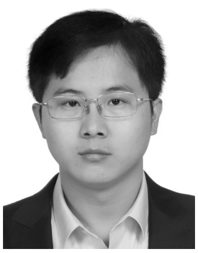

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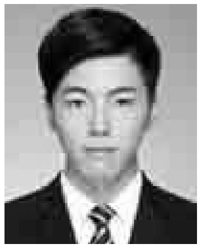

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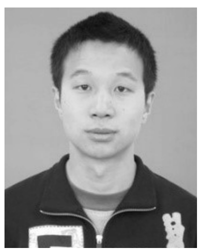

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