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Integrated Traffic Flow and Emission Control Based on FASTLANE and the Multi-Class VT-Macro Model

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***Abstract*— The main goal of this paper is to develop a multi-class traffic flow and emission model that is suited for on-line model-based control. Multi-class traffic flow and emission models take into account the heterogeneous nature of traffic networks. In comparison with single-class models, these models are more accurate. Using more accurate model results in better description of the traffic network. However, this also leads to lower a computation speed when the model is used for on-line model-based control. FASTLANE is a first-order multi-class traffic flow model that is faster than more accurate models (such as METANET). However, FASTLANE does not yet describe emission and fuel consumption. Therefore, we propose to integrate FASTLANE with the VT-macro emission model. This results in a combined FASTLANE and multi-class VT-macro model that describes multi-class traffic flows and emissions and that yields a balanced trade-off between the accuracy and the computation speed. On-line model predictive control is used to obtain a balanced optimization of the total time spent and the total emissions. A case study is implemented to validate the efficiency of the new integrated FASTLANE and multi-class VT-macro model. The simulation results indicate that considering the heterogeneous nature of multi-class traffic leads to a better control performance than single-class models.**

Keywords: Traffic management, FASTLANE, Multi-class VT-macro, Model Predictive Control.

I. INTRODUCTION

Traffic networks are becoming more and more congested due to the increasing traffic demand and the growth of the number of vehicles. This leads to time losses and air pollution problems, which both need to be paid attention to. Many traffic management methods can be applied in traffic networks to solve the congestion and air pollution problems. An on-line model-based control approach is helpful for improving the performance of the traffic network, because it takes into account the evolution of the controlled traffic network. The models used in on-line model-based control affect the speed with which the control signals can be computed. In general, the more accurate the model is, the lower the computation speed will be. Hence, choosing appropriate traffic models is very critical for obtaining a balanced trade-off between accuracy (and thus control performance) and the computation speed.

Traffic networks often contain different classes of vehicles, such as cars, trucks, buses, and vans. Hence, the heterogeneous nature of the traffic flows makes a multi-class model more accurate than a single-class model. There are already some traffic flow models taking into account the heterogeneous nature of the traffic network. Logghe et al. [1] extended the Lighthill-Whitham-Richards (LWR) dynamic traffic flow model to a number of vehicle classes. In this extended LWR model, each class is described by a separate fundamental diagram, and passenger car equivalents (pce) are used to represent different classes of vehicles. Deo et al. [2] developed a multi-class version of the METANET model in which state variables generated based on the length of different classes of vehicles are used to describe the traffic dynamics. FASTLANE [3, 4] is a first-order macroscopic multi-class traffic flow model that is an extension of the LWR model. The main difference between FASTLANE and the extension of the LWR model by Logghe et al. is that it adopts dynamic pce values. The dynamic pce includes the difference between the space occupied by vehicles in free flow and congested flow. Compared with the constant pce, this provides a better description of the heterogeneous nature of multi-class traffic flow.

For the reduction of emissions, appropriate emission models are necessary. The VT-macro model [5] was built based on the integration of the VT-micro model [6] and the METANET model [7, 8]. It is a macroscopic model that yields the emissions and fuel consumption of traffic flows. When applying VT-macro in a multi-class setting, a multi-class version needs to be developed. In order to realize the reduction of emissions of multi-class traffic flow, we propose an integrated FASTLANE and multi-class VT-macro model. The FASTLANE model is faster than more accurate higher-order multi-class traffic flow model (e.g. METANET). Besides, VT-macro model is a fast emission model. Therefore, these two models should result in an acceptable computation speed.

Many performance indications can be considered when controlling traffic networks. The Total Time Spent (TTS) is the total time that all vehicles need to leave the network, and the Total Emissions (TE) is the amount of emissions that all vehicles in the network generate before they leave. The traffic control objectives may be conflicting according to traffic conditions [9]. In this paper, we aim to find a balanced trade-off between TTS and TE. Note, however, that the approach that we proposed is generic, and it can also accommodate other performance criteria. With the integrated FASTLANE and multi-class VT-macro model as prediction models, we can then use Model Predictive Control (MPC) to optimize TTS and TE.

This paper is organized as follows. In Section II, we present the FASTLANE model and the VT-macro model. Then we propose the integrated FASTLANE and multi-class VT-macro model in Section III. In Section IV, we develop on-line MPC based on the integrated FASTLANE and multi-class VT-macro model. After that, a case study is implemented in Section V to show the efficiency of the proposed integrated FASTLANE and multi-class VT-macro model for model-based on-line traffic control. We give the conclusions and several topics for future research in Section VI.

II. Traffic flow and emission models

A. FASTLANE

FASTLANE [3, 4] is a first-order multi-class traffic flow model. A FASTLANE network is represented by links (indexed by m), where each link is divided into homogeneous cells (indexed by i). We use the index c to denote vehicle classes.

FASTLANE is derived from the LWR model, the main difference being that FASTLANE uses dynamic pce. Dynamic pce can be characterized as follows. The space occupied by a vehicle is decided by its length and the distance to the next vehicle. The distance between two vehicles is different between in free flow and in congested flow. In the free-flow regime, the distance between two adjacent vehicles is often larger than their lengths. However, in a congested-flow regime, the distance between two adjacent vehicles is usually smaller than their lengths. The difference is usually not considered in the traditional constant pce models (such as the multi-class LWR model of Logghe et al.). In FASTLANE, this difference is represented by the dynamic pce. The dynamic pce value is a function of the gross stopping distance, the class-specific minimum headway, and the traffic flow speed:

$$\eta_{m,i,c} = \frac{s_c + T_{h,c} \cdot v_{m,i,c}}{s_1 + T_{h,1} \cdot v_{m,i,1}} \tag{1}$$

where s_c is the class-specific gross stopping distance of vehicles of class c, $T_{h,c}$ is the class-specific minimum time headway of vehicles of class c, and $v_{m,i,c}$ is the speed of vehicles of class c in cell i of link m. The index 1 represents the reference class (i.e. passenger car in the FASTLANE model).

The class-specific speed is

$$v_{m,i,c} = V_c(\rho^{\mathrm{efc}}_{m,i}) \tag{2}$$

with

$$\rho^{\mathrm{efc}}_{m,i} = \sum_{c=1}^{n_{\mathrm{c}}} \eta_{m,i,c}\rho_{m,i,c} \tag{3}$$

where V_c is the class-specific equilibrium speed, $\rho^{\mathrm{efc}}_{m,i}$ is the effective density (in pce/km/lane) in cell i of link m, $\rho_{m,i,c}$ is density (in vehicle/km/lane) of vehicles of class c in cell i of link m, and n_{c} is the number of vehicle classes.

We consider the discrete-time form of FASTLANE, since we use it in MPC in this paper. The discrete-time form of (3) that we apply is

$$\rho^{\mathrm{efc}}_{m,i}(k) = \sum_{c=1}^{n_{\mathrm{c}}} \eta_{m,i,c}(k-1)\rho_{m,i,c}(k) \tag{4}$$

where k is the time instant $t = KT$, and T is the simulation time step.

The flow of vehicles of class c in cell (m,i) is

$$q_{m,i,c}(k) = \mu_m \rho_{m,i,c}(k) v_{m,i,c}(k) \tag{5}$$

where μ_m is the number of lanes of link m.

The class-specific speed function is defined as follows:

$$V_c(\rho^{\mathrm{efc}}_{m,i}(k)) = \begin{cases} v^{\mathrm{free}}_{m,c} - \rho^{\mathrm{efc}}_{m,i}(k)\frac{(v^{\mathrm{free}}_{m,c}-v^{\mathrm{crit}}_{m,c})}{\rho^{\mathrm{crit}}_m} & \text{for } \rho^{\mathrm{efc}}_{m,i}(k) < \rho^{\mathrm{crit}}_m \\ \frac{v^{\mathrm{crit}}_{m,c}\rho^{\mathrm{crit}}_m}{\rho^{\mathrm{efc}}_{m,i}(k)}\left(1 - \frac{\rho^{\mathrm{efc}}_{m,i}(k)-\rho^{\mathrm{crit}}_m}{\rho^{\mathrm{jam}}_m-\rho^{\mathrm{crit}}_m}\right) & \text{for } \rho^{\mathrm{efc}}_{m,i}(k) \geq \rho^{\mathrm{crit}}_m \end{cases} \tag{6}$$

in which $v^{\mathrm{free}}_{m,c}$ is the free flow speed in link m for vehicle class c, $v^{\mathrm{crit}}_{m,c}$ is the critical speed, ρ^{crit}_m is the critical density in pce/km/lane, and ρ^{jam}_m is the effective maximum density in pce/km/lane.

The density update equation used in FASTLANE is

$$\rho_{m,i,c}(k+1) = \rho_{m,i,c}(k) + \frac{T}{L_m\mu_m}\left(q^{i-1,i}_{m,c}(k) - q^{i,i+1}_{m,c}(k)\right) \tag{7}$$

where, $q^{i-1,i}_{m,c}$ is the flow from cell $i-1$ to cell i, $q^{i,i+1}_{m,c}$ is the flow from cell i to cell $i+1$, and L_m is the cell length. The following relation should hold [3]:

$$\frac{T}{L_m} \geq \max_{c=1,\cdots,n_{\mathrm{c}}}\{v^{\mathrm{free}}_{m,c}\} \tag{8}$$

The traffic demand of cell i of link m is distributed according to the traffic composition ratios on cell i, which are defined as

$$\lambda_{m,i,c}(k) = \frac{\eta_{m,i,c}(k)q_{m,i,c}(k)}{\sum_{c=1}^{n_{\mathrm{c}}}\eta_{m,i,c}(k)q_{m,i,c}(k)} \tag{9}$$

The class-specific flow between cell i and $i+1$ is

$$q^{i,i+1}_{m,c}(k) = \frac{1}{\eta_{m,i,c}(k)}\min\left(D_{m,i,c}(k), \lambda_{m,i,c}(k)S_{m,i+1}(k)\right) \tag{10}$$

where the demand and supply functions are

$$D_{m,i,c}(\rho^{\mathrm{efc}}_{m,i}(k)) = \begin{cases} \rho_{m,i,c}(k)V_c(\rho^{\mathrm{efc}}_{m,i}(k))\mu_m & \text{for } \rho^{\mathrm{efc}}_{m,i}(k) < \rho^{\mathrm{crit}}_m \\ v^{\mathrm{crit}}_{m,c}\rho^{\mathrm{crit}}_m\mu_m & \text{for } \rho^{\mathrm{efc}}_{m,i}(k) \geq \rho^{\mathrm{crit}}_m \end{cases} \tag{11}$$

$$S_{m,i}(\rho^{\text{efc}}_{m,i}(k)) = \begin{cases} v^{\text{crit}}_{m,c}\rho^{\text{crit}}_{m}\mu_m & \text{for } \rho^{\text{efc}}_{m,i}(k) < \rho^{\text{crit}}_{m} \\ \rho^{\text{efc}}_{m,i}(k)V_c(\rho^{\text{efc}}_{m,i}(k))\mu_m & \text{for } \rho^{\text{efc}}_{m,i}(k) \geq \rho^{\text{crit}}_{m} \end{cases} \tag{12}$$

There are three types of nodes in traffic networks: link-to-link nodes, merge nodes, and diverge nodes. Fig. 1 is a sketch of these three kinds of nodes.

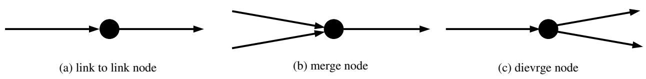

Fig. 1. Sketch of three kinds of nodes

For a link-to-link node, the flow from one cell to its adjacent cell is computed through (10). For a merge node, the flow is given as

$$q_{a,b,c}(k) = \frac{1}{\eta_{a,c}(k)} \min\Big(D_{a,c}(k), \kappa_a \lambda_{a,c}(k) S_b(k)\Big) \tag{13}$$

$$\kappa_a = \frac{C_a}{\sum_{\chi \in A_b} C_\chi} \tag{14}$$

where the index a denotes an incoming link of the incoming link, A_b is the set of all incoming links that are connected to the downstream link b, and where the downstream supply is distributed according to the proportion κ_a, which is computed through the effective capacities (in pce) of the incoming links, and C_a is the effective capacity of link a. Besides, if the demand of one incoming link is less than the given supply, the remaining supply is assigned to other links.

As for a diverge node, the demand has to be assigned to two or more downstream links. The flow equation is as follows:

$$q_{a,b,c}(k) = \frac{1}{\eta_{a,c}(k)} \min\Big(\gamma_b D_{a,c}(k), \lambda_{a,c}(k) S_b(k)\Big) \tag{15}$$

in which b is one of the outgoing links, γ_b is the turn fraction for link b (the upstream demand is assigned according to this turn fraction).

B. VT-macro model

The VT-macro model [5] is a macroscopic emissions and fuel consumption model. Currently, the VT-macro model is still single-class. It is derived from the VT-micro model [6], which describes the emissions and fuel consumption of individual vehicles. The estimation of traffic emissions in the VT-micro model needs the speed and acceleration of each vehicle. In the VT-macro model, however, the emissions are estimated based on macroscopic traffic flows, and the speeds and accelerations used are also the macroscopic ones. More specifically, the VT-macro model considers two kinds of accelerations: inter-cell acceleration and cross-cell acceleration, as shown in Fig. 2.

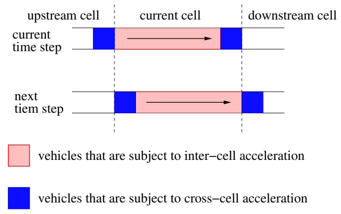

Fig. 2. Inter-cell acceleration and cross-cell acceleration

These accelerations are computed trough the following equations:

$$a^{\text{inter}}_{m,i}(k) = \frac{v_{m,i}(k+1) - v_{m,i}(k)}{T} \tag{16}$$

$$a^{\text{cross}}_{\alpha,\beta}(k) = \frac{v_\beta(k+1) - v_\alpha(k)}{T} \tag{17}$$

in which α and β denote the indices of 2 consecutive cells, on-ramps, or off-ramps. The corresponding numbers of vehicles subject to these two accelerations are

$$n^{\text{inter}}_{m,i}(k) = L_m \mu_m \rho_{m,i}(k) - T q_{m,i}(k) \tag{18}$$

$$n^{\text{cross}}_{\alpha,\beta}(k) = T q_\alpha(k) \tag{19}$$

where $q_{m,i}$ is the outflow of cell i in link m, and q_α is the outflow of the upstream cell α.

The estimations of emissions per time unit in one cell are

$$J^{\text{inter}}_{y,m,i}(k) = n^{\text{inter}}_{m,i}(k) \exp\Big(\tilde{v}^T_{m,i}(k) P_y \tilde{a}^{\text{inter}}_{m,i}(k)\Big) \tag{20}$$

$$J^{\text{cross}}_{y,\alpha,\beta}(k) = n^{\text{cross}}_{\alpha,\beta}(k) \exp\Big(\tilde{v}^T_{\alpha}(k) P_y \tilde{a}^{\text{cross}}_{\alpha,\beta}(k)\Big) \tag{21}$$

where $y \in Y = \{\text{CO}, \text{NO}_\text{x}, \text{HC}\}$, $\tilde{a}^{\text{inter}}_{m,i}$ and $\tilde{a}^{\text{cross}}_{\alpha,\beta}$ are vectors in terms of $\tilde{x} = [1\ x\ x^2\ x^3]^T$, P_y is a model parameter matrix, and the value of this matrix can be found in [6, 10].

III. Integrated FASTLANE and multi-class VT-macro model

A. Extensions of FASTLANE

The original FASTLANE does not include the estimation of queue lengths at the origins. Also, the applying of traffic control measures (such as speed limit and ramp metering) is not discussed. Here we extend the original FASTLANE by including queue length equation, speed limit and ramp metering.

In order to obtain the queue lengths at the origins and on-ramps, We introduce a simple queue equation [7, 8, 11]:

$$w_{o,c}(k+1) = w_{o,c}(k) + T(D_{o,c}(k) - q_{o,c}(k)) \tag{22}$$

where $w_{o,c}$ is the queue length of vehicles of class c at origin(on-ramp) o, $D_{o,c}$ is the demand of the vehicles of class c at the origin o, and $q_{o,c}$ is the outflow of the vehicles of class c at the origin o.

If a dynamic speed limit is applied in cell i of link m, the speed can be estimated through the following equation [11]:

$$v_{m,i,c}(k) = \min(V_c(\rho^{\text{efc}}_{m,i}(k)), (1+\delta) v_{\text{SL},m,i}(k)) \tag{23}$$

in which $v_{\mathrm{SL},m,i}(k)$ is the speed limit, and $(1+\delta)$ is the non-compliance factor that allows for modeling enforced and unenforced speed limit.

According to the above-mentioned concepts, an on-ramp is merge node. If there is a ramp metering at the on-ramp, the on-ramp flow can be defined as

$$q_{a,b,c}(k)=\frac{1}{\eta_{a,c}(k)}\min\Big(r(k)D_{a,c}(k),\kappa_a\lambda_{a,c}(k)S_b(k)\Big) \quad (24)$$

in which a indicates the on-ramp, b indicates the link that is connected to the on-ramp, and $r(k)$ is the ramp metering rate at this on-ramp.

B. Multi-class VT-macro model

Now we propose the integrated FASTLANE and multi-class VT-macro model. The FASTLANE model describes the multi-class traffic flow, and the output state variables of the FASTLANE model are used as the inputs of the multi-class VT-macro model. These output state variables are $v_{m,i,c}(k)$, $\rho_{m,i,c}(k)$, and $q_{m,c}^{i,i+1}(k)$.

The inter-cell and cross-cell accelerations in the multi-class case are given as

$$a_{m,i,c}^{\mathrm{inter}}(k)=\frac{v_{m,i,c}(k+1)-v_{m,i,c}(k)}{T} \quad (25)$$

$$a_{\alpha,\beta,c}^{\mathrm{cross}}(k)=\frac{v_{\beta,c}(k+1)-v_{\alpha,c}(k)}{T} \quad (26)$$

where the index c denotes the vehicle class. The actual numbers of vehicles subject to these two accelerations are

$$n_{m,i,c}^{\mathrm{inter}}(k)=L_m\mu_m\rho_{m,i,c}(k)-Tq_{m,c}^{i,i+1}(k) \quad (27)$$

$$n_{\alpha,\beta,c}^{\mathrm{cross}}(k)=Tq_{\alpha,\beta,c}(k) \quad (28)$$

where $q_{\alpha,\beta,c}$ is the flow from α to β. Based on the equations above, we get the estimates of emissions rates of each class of vehicles in one cell:

$$J_{y,m,i,c}^{\mathrm{inter}}(k)=n_{m,i,c}^{\mathrm{inter}}(k)\exp\left(\tilde{v}_{m,i,c}^{T}(k)P_{y,c}\tilde{a}_{m,i,c}^{\mathrm{inter}}(k)\right) \quad (29)$$

$$J_{y,\alpha,\beta,c}^{\mathrm{cross}}(k)=n_{\alpha,\beta,c}^{\mathrm{cross}}(k)\exp\left(\tilde{v}_{\alpha,c}^{T}(k)P_{y,c}\tilde{a}_{\alpha,\beta,c}^{\mathrm{cross}}(k)\right) \quad (30)$$

where the parameter matrices $P_{y,c}$ are class-specific.

IV. On-line Model Predictive Control

On-line Model Predictive Control (MPC) [12] was used as the control approach in this paper. MPC is based on a dynamic prediction model and a receding horizon approach, and can deal with nonlinear systems, multi-criteria optimization, and constraints. The performance of the controlled system is evaluated by an objective function. This objective function includes the predicted performance of the traffic network over some horizon, which are generated by the prediction model. The optimized control inputs are produced by the controller, and the first element of the control sequence is applied to the traffic network in a receding horizon approach. The closed loop MPC for traffic network is shown in Fig. 3.

In the following control scheme, the newly proposed integrated FASTLANE and multi-class VT-macro model was used as the prediction model. The control measures that we used here are variable speed limits and ramp metering. The prediction horizon is denoted by N_{p}, and the control horizon is denoted by N_{c}. The simulation time step is T, and the controller time step is T_{c}. We also define $M=T/T_{\mathrm{c}}$ that is assumed to be a positive integer.

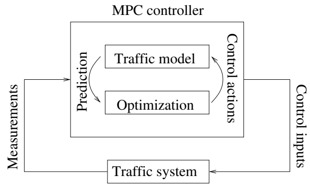

Fig. 3. Closed loop Model Predictive Control

The total time spent (TTS) is estimated as

$$\mathrm{TTS}(k_{\mathrm{c}})=T\sum_{j=k_{\mathrm{c}}M}^{(k_{\mathrm{c}}+N_{\mathrm{p}})M-1}\sum_{c=1}^{C}\left(\sum_{(m,i)\in I_{\mathrm{all}}}\frac{1}{\eta_{m,i,c}(j)}L_m\mu_m\rho_{m,i,c}(j)+\sum_{o\in O_{\mathrm{all}}}w_{o,c}(j)\right) \quad (31)$$

in which I_{all} is the set of all pairs of link and cell indices (m,i) in the network, O_{all} is the set of indices of all origins, $w_{o,c}$ is the queue length of vehicles of class c at the origin o.

The total emissions (TE) of type $y\in Y=\{\mathrm{CO},\mathrm{NO}_x,\mathrm{HC}\}$ can be defined as

$$\mathrm{TE}_y(k_{\mathrm{c}})=T\sum_{j=k_{\mathrm{c}}M}^{(k_{\mathrm{c}}+N_{\mathrm{p}})M-1}\sum_{c=1}^{C}\left[\sum_{(m,i)\in I_{\mathrm{all}}}J_{y,m,i,c}^{\mathrm{inter}}(j)+\sum_{\alpha,\beta\in P_{\mathrm{all}}}J_{y,\alpha,\beta,c}^{\mathrm{cross}}(j)\right] \quad (32)$$

where P_{all} is the set of all pairs of adjacent cells.

The objective function to be optimized by the controller at control step k_{c} is defined as

$$J(k_{\mathrm{c}})=\xi_{\mathrm{TTS}}\frac{\mathrm{TTS}(k_{\mathrm{c}})}{\mathrm{TTS}^{\mathrm{nom}}}+\sum_{y\in Y}\xi_{\mathrm{TE},y}\frac{\mathrm{TE}_y(k_{\mathrm{c}})}{\mathrm{TE}_y^{\mathrm{nom}}}+\xi_{\mathrm{ramp}}\sum_{l=k_{\mathrm{c}}}^{k_{\mathrm{c}}+N_{\mathrm{c}}-1}\sum_{o\in O_{\mathrm{ramp}}}\left(r_{\mathrm{ctrl},o}(l)-r_{\mathrm{ctrl},o}(l-1)\right)^2+\xi_{\mathrm{speed}}\sum_{l=k_{\mathrm{c}}}^{k_{\mathrm{c}}+N_{\mathrm{c}}-1}\sum_{(m,i)\in I_{\mathrm{speed}}}\left(\frac{v_{\mathrm{ctrl},m,i}(l)-v_{\mathrm{ctrl},m,i}(l-1)}{v_{\mathrm{free},m,\mathrm{max}}}\right)^2 \quad (33)$$

in which $\mathrm{TTS}^{\mathrm{nom}}$ is the 'nominal' TTS for some nominal control profile (here we take the 'nominal' TTS as the TTS in no control case), $\mathrm{TE}_y^{\mathrm{nom}}$ is the defined in a similar way with $\mathrm{TTS}^{\mathrm{nom}}$, the variation of control inputs ramp rates and speed limits are penalized through the third and forth terms of (33), O_{ramp} represents all the metered origins, $r_{\mathrm{ctrl},o}$ is the ramp metering rate of origin o at control steps, $v_{\mathrm{ctrl},m,i}$ is the speed limit of vehicles of class c in cell i of link m at control steps, and $v_{\mathrm{free},m,\mathrm{max}}=\max_c v_{m,c}^{\mathrm{free}}$, moreover, ξ_{TTS}, $\xi_{\mathrm{TE},y}$, ξ_{ramp}, and ξ_{speed} are nonnegative weights.

V. Case study

A. Network

A benchmark network [11] is used for case study in this paper. The network includes one origin, one destination, one single-lane on-ramp and two double-lane links. The links are divided into homogeneous cells. The first link contains four cells, and the second links contains two cells. The on-ramp is connected to the first cell of the second link. The network is shown in the Fig. 4.

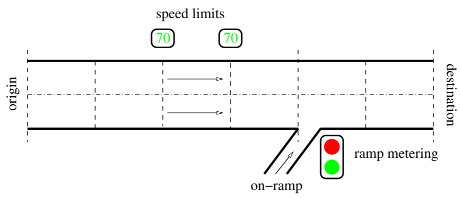

Fig. 4. The benchmark network

We select parameters according to [3, 11, 13]. Two classes of vehicles (class 1: cars; class 2: trucks) are considered with the following parameters: $v_1^{\text{crit}} = 106.34$ km/h, $\delta_1 = 0.12$, $\rho_1^{\text{crit}} = 34.7349$ veh/km/lane, $\rho_1^{\text{jam}} = 175$ veh/km/lane, $s_1 = 7.5$ m, $T_{h,1} = 1.2$ s, $C_1^{\text{main}} = 2034$ veh/h/lane; $v_2^{\text{crit}} = 82.80$ km/h, $\delta_2 = 0.0533$, $\rho_2^{\text{crit}} = 18.9261$ veh/km/lane, $\rho_2^{\text{jam}} = 75$ veh/km/lane, $s_2 = 17.5$ m, $T_{h,2} = 1.8$ s, $C_2^{\text{main}} = 990$ veh/h/lane.

The capacity of the on-ramp is $C^{\text{on ramp}} = C^{\text{main}} - 100$pce. The parameters for single-class model are the convex combination of parameters of class 1 and class 2 obtained as follows:

$$\text{Parameters}_{\text{nom}} = \theta^1_{\text{nom}}\text{Parameters}_1 + (1-\theta^1_{\text{nom}})\text{Parameters}_2.$$

Here we take $\theta^1_{\text{nom}} = 0.7$. The length of each cell is: $L = 1$ km. The queue length at the on-ramp O_2 may not exceed 100 pce (passenger car equivalents). Besides, the destination D_1 has an unrestricted outflow.

The nominal model parameter matrices in VT-macro model $P^{\text{nom}}_{\text{CO}}$, $P^{\text{nom}}_{\text{HC}}$, and $P^{\text{nom}}_{\text{NO}_x}$ are taken from [10]. We assume:

$$P_1^{\text{CO}} = 1.1P^{\text{CO}}_{\text{nom}} \quad P_1^{\text{HC}} = 1.1P^{\text{HC}}_{\text{nom}} \quad P_1^{\text{NO}_x} = 1.1P^{\text{NO}_x}_{\text{nom}}$$

The parameter matrices for class 2 are computed through $P_2 = \frac{P_{\text{nom}} - \theta_{\text{nom}}P_1}{1-\theta_{\text{nom}}}$.

The control parameters are $\xi_{\text{TTS}} = 1$ $\xi_{\text{TE},y} = 0.1$ $\xi_{\text{ramp}} = \xi_{\text{speed}} = 0.01$, $T = 10$ s, $T_c = 60$ s, $N_p = 7$, $N_c = 5$. The prediction horizon is in the order of the typical travel time through the network. A shorter prediction cannot account for the whole response of the network, and lead to insufficient control actions. Moreover, longer prediction horizon takes the future demand too much into account, as such the performance will be degraded. Besides, a large difference between N_p and N_c may result in a lower performance, since the control inputs for this period equal the last sample of the control sequence, while only the first sample of the control sequence is applied to the network. A control horizon $N_c = 5$ is necessary here.

B. Scenarios

We take the typical demand scenario from [11]. The total simulation time is 2.5 h. The demand scenario is shown in Fig. 5. Different proportions for the two classes of vehicles

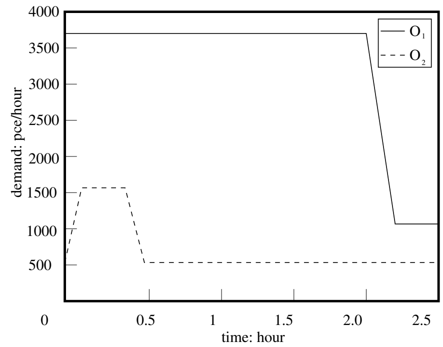

Fig. 5. The original demand scenario

are considered: $\theta_1 \in \{0.1, 0.3, 0.7\}$. Besides, we consider three control cases:

- No control.
- MPC with single-class prediction models.
- MPC with multi-class prediction models.

FASTLANE and the multi-class VT-macro model are used as simulation models in MPC.

C. Results

The simulation results are shown in Tables 1-3. The TTS, TE and J listed in Table 1-3 are calculated for the entire simulation period of 2.5 h.

Table 1 Simulation results ($\theta_1 = 0.1$)

Scenario	TTS (veh·h)	TE (kg)	J
No control	1246.9	687.8865	33.4351
Single-class MPC	1283.5	695.8364	34.3791
Multi-class MPC	1107.7	651.7231	29.8238

Table 2 Simulation results ($\theta_1 = 0.3$)

Scenario	TTS (veh·h)	TE (kg)	J
No control	1422.9	541.1609	33.2376
Single-class MPC	1373.4	532.6754	32.1203
Multi-class MPC	1313.3	511.2108	30.7212

Table 3 Simulation results ($\theta_1 = 0.7$)

Scenario	TTS (veh·h)	TE (kg)	J
No control	1751.4	249.6476	32.9837
Single-class MPC	1835.4	226.3983	34.2790
Multi-class MPC	1744.6	232.9226	32.7288

According to Table 1-3, we can see that multi-class MPC results in a much better control performance than single-class MPC. This means that multi-class MPC results in smaller J than single-class MPC: 4.21%-13.62%. Sometimes applying single-class model even leads to worse results than no-control case. For the given setting here, we can conclude that taking into account heterogeneous nature leads to a better performance in on-line model based control.

VI. Conclusions

In this paper, we have introduced a multi-class extension of the VT-macro model. We have also integrated this model with the multi-class traffic flow model FASTLANE. The outputs of FASTLANE are used to estimate the accelerations for the multi-class VT-macro model. We have also extended the FASTLANE model by including a queue length equation and control measures (speed limits and ramp metering). Finally, a case study was implemented to illustrate the potential benefits of the newly developed models using Model Predictive Control (MPC). Multi-class MPC and single-class MPC were both implemented for comparison. Based on the obtained results for the given settings, we can see that taking into account the multi-class nature of traffic network results in a much better control performance.

Based on the research that we have done, the following topics are going to be studied: comparison with traffic control using more accurate multi-class traffic flow model (e.g., multi-class METANET), applying more accurate emission model. Thus, we aim to investigate different computation speed and accuracy when applying simple fast model and accurate slow model separately.

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