

The role of trip lengths in control strategies and Macroscopic Fundamental Diagram traffic models

Sérgio F. A. Batista^{*1}, Deepak Ingole^{†1}, Ludovic Leclercq^{‡1} and
Monica Menendez^{§2,3}

¹Univ. Lyon, IFSTTAR, ENTPE, LICIT, F-69675, Lyon, France

²Division of Engineering, New York University Abu Dhabi, United
Arab Emirates

³Tandon School of Engineering, New York University, USA

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1 Introduction

2 Aggregated traffic models were introduced by Godfrey (1969) and later revisited by
3 Daganzo (2007) and Geroliminis & Daganzo (2008). These traffic models require
4 the partition of the city network (see e.g., Saeedmanesh & Geroliminis, 2016, 2017,
5 Lopez et al., 2017, Casadei et al., 2018) into regions, where the traffic conditions are
6 approximately homogeneous. Such partition defines the regional network. In each
7 region, the traffic states are measured through the vehicles' accumulation $n(t)$ and
8 are regulated by a Macroscopic Fundamental Diagram (MFD). The MFD reflects
9 the relationship between the average circulating flow of vehicles and the average
10 density in the region.

11 The regional network definition brings new challenges. Figure 1 depicts the
12 challenge of scaling up trips to the regional network. The green and blue trips follow
13 a sequence of links in the city network, with a fixed length. The green and blue
14 trips cross a different sequence of regions, following the city network partitioning.
15 The ordered sequence of crossed regions by a trip is called regional path. The green
16 and blue trips describe different travel distances inside each region, as highlighted
17 in the gray region. Therefore, regional paths are characterized by distributions
18 of trip lengths, containing information of the plausible travel distances in the city

*✉ sergio.batista@ifsttar.fr

†✉ deepak.ingole@entpe.fr

‡✉ ludovic.leclercq@entpe.fr

§✉ monica.menendez@nyu.edu

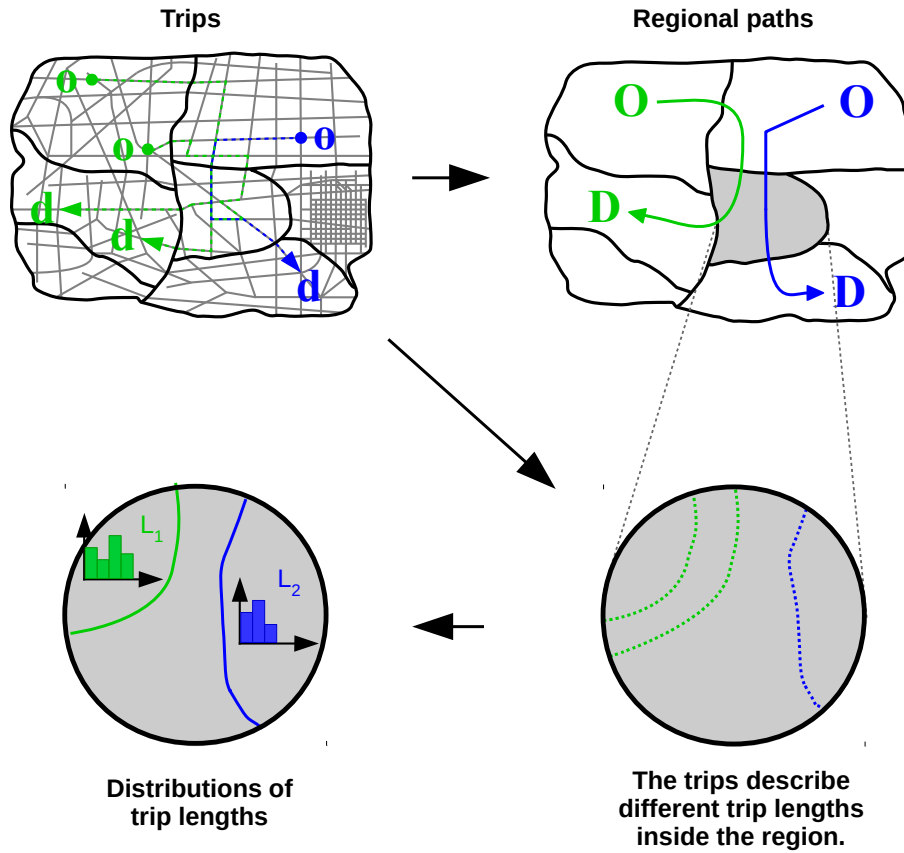


Fig. 1 – The scale up of trips into regional paths, that are characterized by trip length distributions.

1 network. Batista et al. (2018) and Batista et al. (in prep.) propose a methodological
 2 framework to calculate trip length distributions based on a set of trips and different
 3 levels of information from the regional network. The first level calculates trip length
 4 distributions considering the travel distances of all trips crossing one region. This
 5 assigns a common trip length distribution for all regional paths that cross the same
 6 region, independently of their Origin and Destination (OD). We refer to this level as
 7 $M_{standard}$. The most detailed level only considers the trips that define the same
 8 regional path. This allows to derive different trip lengths for all regional paths that
 9 cross the same region. We refer to this level as $M_{reference}$. The authors show that
 10 $M_{standard}$ is not able to capture the trip lengths variability of all regional paths
 11 crossing the same region. Moreover, they also show that the calibration of the trip
 12 lengths clearly influences the modeled traffic dynamics inside the regions.

13 Up to now, most of the MFD applications have been designed to test control
 14 algorithms or design perimeter control strategies. Daganzo (2007), Keyvan-
 15 Ekbatani et al. (2012) and Ekbatani et al. (2013) tested perimeter control strategies
 16 for a one region network, where all vehicles were assigned a common average travel
 17 distance. Some theoretical studies (see e.g., Haddad, 2017, Zhong et al., 2017, Yang

1 et al., 2018) focused on the outflow-MFD application, where all vehicles were as-
 2 signed the same trip length. Aboudolas & Geroliminis (2013) and Kouvelas et al.
 3 (2017) tested perimeter control strategies in real city networks, but an average trip
 4 length for all regions was also considered.

5 Research contribution

6 In this paper, we propose to investigate the role of the trip lengths calibration
 7 for perimeter control strategies. The goal is to quantify the effects of improper
 8 assumptions on the travel distances in the regions on Model Predictive Control
 9 (MPC) based control strategies. In this extended abstract, we discuss some initial
 10 and preliminary results obtained by a Proportional-Integral (PI) gating control
 11 scheme on a real network.

12 Test scenario and methodological framework

13 The test network is depicted in Figure 2 (a). It includes the 3rd and 6th districts of
 14 Lyon and the city of Villeurbanne (France). The network has 3127 nodes and 3363
 15 links and is divided into seven regions. Figure 2 (b) depicts the MFD functions.
 16 They were calculated by assuming a bi-parabolic shape to fit microscopic simulation
 17 data obtained from Symuvia (Leclercq, 2007).

18 The calculation of the trip lengths and regional paths are based on a virtual
 19 trips set in the city network. To gather this set, we randomly sample 3 million
 20 origin and destination nodes in the city network and calculate the shortest-path in
 21 distance between each of them. To obtain the regional paths, we filter all trips by
 22 the specific sequence of regions they cross. For each regional OD pair, the regional
 23 paths are ranked according to the number of trips they have associated. For our case
 24 study, we consider three OD pairs: 1-7; 4-2; and 6-4. To define the regional choice
 25 set for each OD pair, we gather the two regional paths with the largest number of
 26 trips associated. We calculate the trip lengths distributions following the $M_{standard}$
 27 and $M_{reference}$ described in the Introduction (see also Batista et al., 2018, in prep.,
 28 , for more details). The regional paths and demand assignment coefficients are
 29 listed in Table 1. The average trip lengths calculated by $M_{standard}$ and $M_{reference}$
 30 are listed in Table 2. The demand scenarios for the three OD pairs are shown in
 31 Figure 2 (c). The traffic states are simulated through an accumulation-based MFD
 32 model (Daganzo, 2007, Geroliminis & Daganzo, 2008), for a total simulation period
 33 of $T = 20000$ seconds.

34 Our goal is to control the maximum vehicles' accumulation in region 3 (i.e.
 35 $(n_3(t))$). For this purpose, we designed a gating control composed by three PI
 36 controllers with an anti-windup scheme to track the desired set-point, i.e. $(n_3(t))$.
 37 Figure 3 depicts the PI-based gating control scheme that is implemented. The
 38 inflows of regional paths 1 – 3 – 5 – 7 ($I_{3,1}^1$), 4 – 3 – 2 ($I_{3,2}$) and 6 – 5 – 3 – 4 ($I_{3,3}$)
 39 are manipulated by the PI controller before entering region 3. The new inflows are
 40 $u_{3,1}(t)$, $u_{3,2}(t)$ and $u_{3,3}(t)$. The manipulation by the controller is done such that
 41 $n_3(t)$ is maintained at the set-point. The outflows ($o_{3,1}$, $o_{3,2}$, $o_{3,3}$) will continue to the
 42 next regions in the sequence of the corresponding regional paths. In this example,

¹The first subscript refers to the region that is being controlled. The second subscript refers to the regional paths will cross region 3.

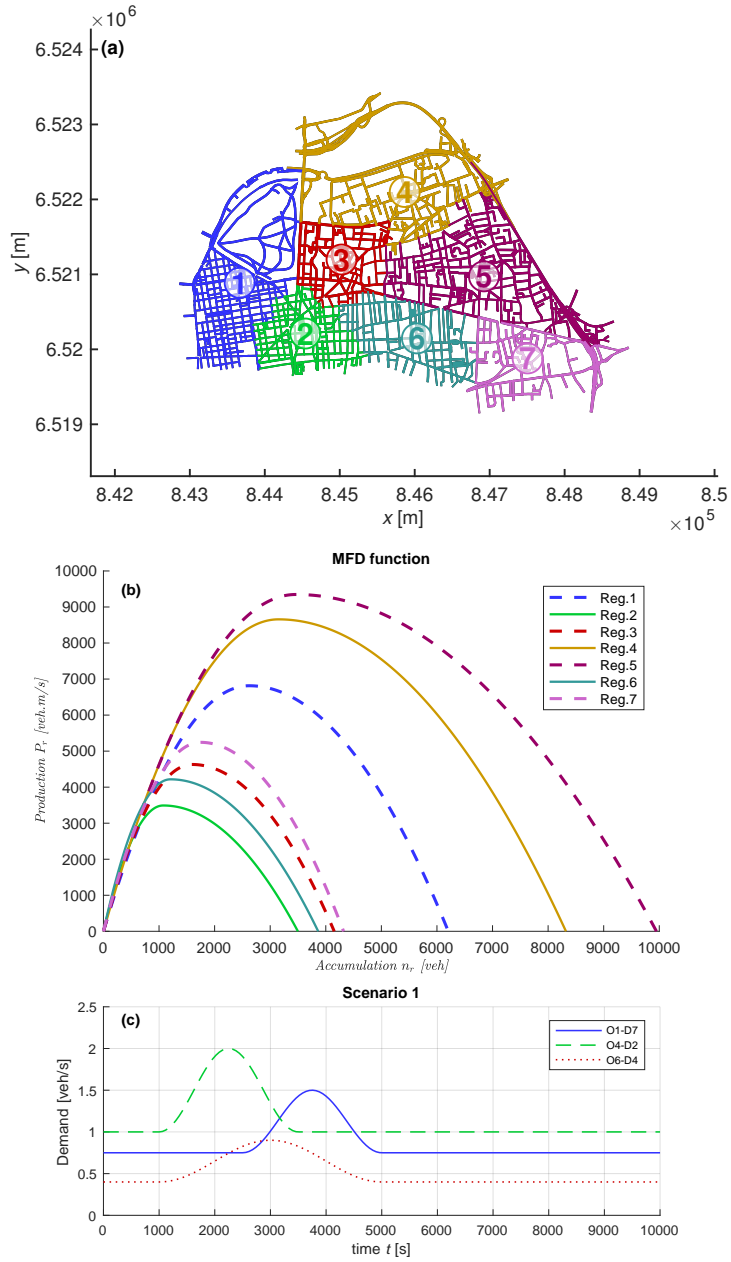


Fig. 2 – (a) Villeurbanne and the 3^d and 6th districts of Lyon (France) traffic network, divided into seven regions. (b) MFD function of each region. (c) Demand scenarios.

O	D	Regional path	Assignment coefficient
1	7	1-2-6-7	0.15
		1-3-5-7	0.85
4	2	4-1-2	0.25
		4-3-2	0.75
6	4	4-3-2	0.00
		6-5-3-4	1.00

Tab. 1 – Regional paths and the assignment coefficients used for this study.

Method	Regional path	Region						
		1	2	3	4	5	6	7
Standard	1-2-6-7	987	649	~	~	~	694	926
	1-3-5-7	987	~	880	~	1042	~	926
	4-1-2	987	649	~	1347	~	~	~
	4-3-2	~	649	880	1347	~	~	~
	6-5-3-4	~	~	880	1347	1042	694	~
Reference	1-2-6-7	788	1121	~	~	~	1424	676
	1-3-5-7	927	~	1297	~	1032	~	1142
	4-1-2	2761	335	~	2227	~	~	~
	4-3-2	~	708	1049	1191	~	~	~
	6-5-3-4	~	~	458	733	861	584	~

Tab. 2 – Average trip lengths (m) calculated by the methods $M_{standard}$ and $M_{reference}$.

- 1 we assume that the set of regional paths and trip lengths remain unchanged. In
- 2 the full paper, we will consider the vehicles' re-routing due to the control effects on
- 3 the travel times and time-dependent trip lengths. The proportional ($k_p = 1$) and
- 4 integral ($k_i = 0.05$) gains of the PI controller are obtained using trial and error
- 5 methods.

6 Preliminary results and discussion

- 7 Figure 4 depicts the evolution of the vehicles' accumulation $n(t)$ during the simu-
- 8 lation period T , for all seven regions. We first briefly analyze the results for the
- 9 uncontrolled cases, that are represented by the solid curves. We observe that the
- 10 $n(t)$ peak between ~ 3000 - 7000 seconds, is larger for the case of $M_{reference}$ compared
- 11 to $M_{standard}$. This happens because the average trip lengths calculated through
- 12 $M_{reference}$ for regional paths $1 - 2 - 6 - 7$ and $1 - 3 - 5 - 7$ are larger than the
- 13 ones calculated through $M_{standard}$ (see Table 2). The speed-MFD is the same for
- 14 all vehicles traveling in region 1. Therefore, they need more time to complete their

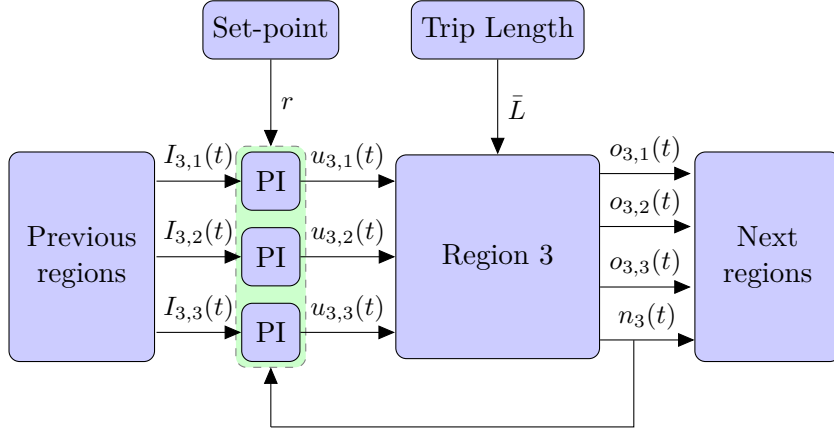


Fig. 3 – Representation of closed-loop gating control using PI controllers.

1 trips for $M_{reference}$ as the travel distance is longer, increasing the accumulation.
2 The results for the controlled cases are represented by the dashed lines. We
3 are gating the inflow of the three regional paths that cross region 3 (see Table 1
4 for the list of these regional paths). When $n_3(t)$ reaches 500 vehicles,
5 start queuing in regions 1, 4 and 5. These are the previous adjacent regions to 3
6 in the three regional path sequences. The vehicles' accumulation in these regions
7 increases compared to the uncontrolled cases. This influences the traffic dynamics in
8 the regions. This happens especially when the accumulation reaches the congestion
9 branch of the MFD, where priority rules are applied.

10 Figure 2 (c) depicts one demand peak per OD pair, each happening at dif-
11 ferent time instants. From these three demand peaks, vehicles traveling on regional
12 path 4 – 3 – 2 are the first to arrive to region 3. They are allowed to enter region 3,
13 until $n_3(t) = 500$ vehicles. The travel distances for region 3 assigned by $M_{reference}$
14 are larger than the ones by $M_{standard}$. Vehicles are then queuing for a longer period
15 of time in region 4, for the case of $M_{reference}$ compared to $M_{standard}$. This leads to
16 a larger accumulation for $M_{reference}$ than $M_{standard}$ in region 4. The next demand
17 peaks to arrive are traveling on regional paths 6 – 5 – 4 – 3 and 1 – 3 – 5 – 7,
18 respectively. Since region 3 is already at its maximum targeting accumulation, ve-
19 hicles traveling on these two regional paths will be queuing in regions 5 and then 1.
20 This leads to larger accumulations for these two regions for the case of $M_{reference}$
21 compared to $M_{standard}$.

22 These results highlight that the trip lengths calibration is very important
23 and play an important role in the spreading of congestion to adjacent regions as
24 well as on the regional traffic dynamics. In the full paper, we will analyse the role
25 of the trip lengths estimation on the MPC.

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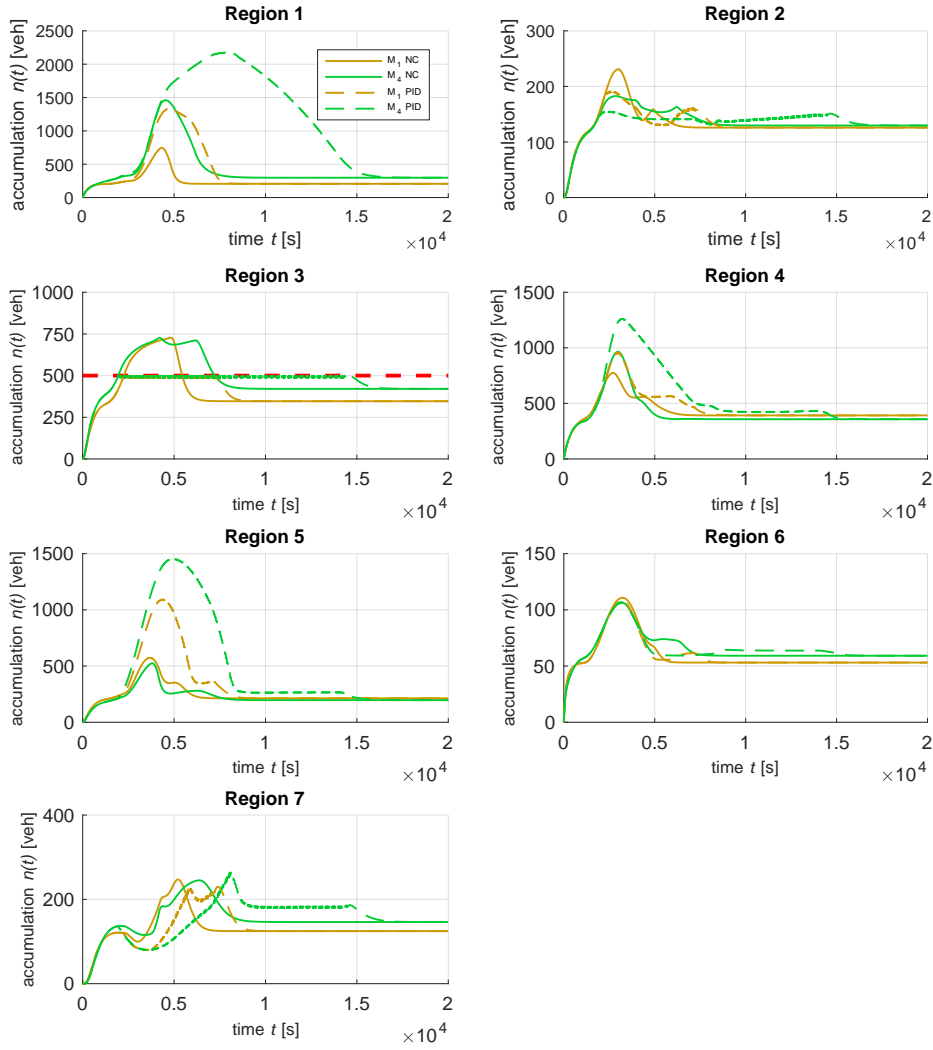


Fig. 4 – Evolution of the vehicles' accumulation $n(t)$ for all seven regions.

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