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# On the calibration of time-varying trip length distributions for the aggregated traffic models

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## 1 Abstract

One of the key questions for Macroscopic Fundamental Diagram traffic models lies in the calibration of the trip lengths, i.e. the travel distances of vehicles in the regions. Few studies in the literature have attempted to propose methodological frameworks to calibrate the trip lengths. Batista et al. (2019) propose a framework to explicitly calculate trip length distributions. However, they do not consider the influence of the traffic conditions on the trip lengths. In this paper, we propose to extend their methodological framework to determine time-varying trip length distributions according to the changes in the traffic conditions.

## 1 Introduction

Aggregated traffic models at the city network level were early introduced by Godfrey (1969) and later reconsidered by Daganzo (2007) and Geroliminis & Daganzo (2008). These traffic models, although designed for urban areas require the partition of the city network (Figure 1 (a)) into regions (Figure 1 (b)) (see e.g., Saeedmanesh & Geroliminis, 2016, 2017, Lopez et al., 2017, Casadei et al., 2018, Ambühl et al., 2019), where the traffic conditions are approximately homogeneous. Figure 1 (c) shows the regional network that corresponds to the city network partitioning. Let  $X$  be the set of regions that define the regional network. In each region, the traffic

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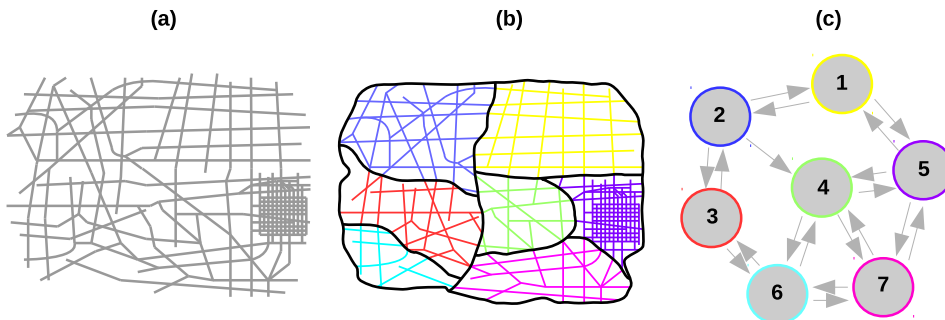


Fig. 1 – (a) *City network*. (b) *Partition of the city network*. (c) *Regional network*.

1 states are regulated by a Macroscopic Fundamental Diagram (MFD). An MFD is  
 2 a relationship between the average circulating flow of vehicles and the average den-  
 3 sity. The traffic dynamics for a single region  $r \in X$  are governed by a conservation  
 4 equation, where the vehicles' accumulation  $n_r(t)$  depends on the balance between  
 5 the inflow ( $Q_{in,r}(t)$ ) and the outflow ( $Q_{out,r}(t)$ ):

$$\frac{dn_r}{dt} = Q_{in,r}(t) - Q_{out,r}(t), t > 0 \quad (1)$$

6 There are two kinds of MFD models that can be distinguished in the liter-  
 7 ature, depending on the assumptions made on  $Q_{out,r}(t)$ : the accumulation-based  
 8 model (Daganzo, 2007, Geroliminis & Daganzo, 2008); and the trip-based model  
 9 (Arnott, 2013, Lamotte & Geroliminis, 2016, Mariotte et al., 2017, Mariotte &  
 10 Leclercq, 2018).

11 One of the main components of MFD models is the setting of the vehicles'  
 12 trip lengths, i.e. the travel distances in the regions. Most applications of the MFD  
 13 models have been designed for testing control algorithms and strategies, where  
 14 the authors consider a constant average travel distance for all vehicles in the same  
 15 region (see e.g., Daganzo, 2007, Keyvan-Ekbatani et al., 2012, Ekbatani et al., 2013,  
 16 Haddad, 2017, Zhong et al., 2017, Yang et al., 2018). Aboudolas & Geroliminis  
 17 (2013) and Kouvelas et al. (2017) tested perimeter control strategies in real city  
 18 networks, but the authors also consider a constant average travel distance for all  
 19 vehicles traveling in the same region. Up to now, little attention has been paid in  
 20 the literature to the challenging task of the trip lengths calibration for MFD models  
 21 applications.

22 Figure 2 depicts the scale-up of trips in the city network into paths in the  
 23 regional network as well as the associated challenges. One can observe that the  
 24 green and blue trips cross a different sequence of regions, following the definition of  
 25 the city network partitioning. This ordered sequence of crossed regions by a trip is  
 26 called regional path. The green and blue trips have different travel distances inside  
 27 each crossed region. This leads to different travel distances associated to the same  
 28 regional path. They are then characterized by distributions of trip lengths inside  
 29 each crossed region. An example is depicted in Figure 2 for the green regional path  
 30 inside the gray region. In fact, the trip length distribution associated to the green  
 31 regional path in the gray region contains the information of the plausible travel

1 distances of the green trips in the city network. The question is how to properly  
2 calibrate the trip lengths distributions based on the information of trips in the city  
3 network. Yildirimoglu & Geroliminis (2014) proposed a methodological framework  
4 to implicitly estimate time-varying average trip lengths. Recently, Batista et al.  
5 (2018) and Batista et al. (2019) went one step further and proposed a methodology  
6 to explicitly calculate distributions of trip lengths for the calibration of dynamic  
7 MFD models. The methodology is based on trip patterns in the city network and  
8 different levels of information from the regional network. Since the true trip patterns  
9 in the city network are unknown and change over time, the authors constructed a  
10 virtual set of trips. For this, they randomly sampled a large number of origin-  
11 destination (od) pairs in the city network and calculated the shortest-paths in  
12 terms of distance for each pair. These virtual trips were then filtered according to  
13 different levels of information from the regional network. The latter ranged from  
14 no information about the previous and next regions to be traveled by the trips, to  
15 their associated regional path. The first level of information calculates trip length  
16 distributions considering the travel distances of all trips that cross one region. It  
17 assigns a common average trip length for all vehicles traveling in the same region,  
18 independent of their regional path. The most detailed level only considers trips  
19 that define the same regional path. This allows to determine a different trip length  
20 distribution for all regional paths that cross the same region. The authors showed  
21 that the first level of information is not able to capture the trip length variability  
22 of all regional paths crossing the same region. Moreover, they also showed that  
23 the trip lengths calibration clearly influences the modeled traffic dynamics in the  
24 regions. The authors concluded that filtering the trips by their associated regional  
25 path to explicitly calculate the trip length distributions should be considered.

26 Yildirimoglu & Geroliminis (2014) and Leclercq et al. (2015) showed that  
27 the vehicles' trip lengths are influenced by the traffic states. In this paper, we  
28 revisit the methodological framework proposed by Batista et al. (2018) and Batista  
29 et al. (2019) to explicitly determine trip length distributions for the calibration of  
30 MFD models. We propose to extend this framework for time-varying trip length  
31 distributions. In Sect. 2, we review in more detail the methodological framework  
32 proposed by Batista et al. (2018) and Batista et al. (2019). We also discuss the  
33 extension of this methodological framework to determine time-varying trip length  
34 distributions. In Sect. 3, we test the proposed extension on the 6<sup>th</sup> district Lyon  
35 network, that is divided into four regions. We discuss some preliminary results for  
36 two regional paths. In Sect. 4, we outline the conclusions of this paper.

## 37 **2 Methodological framework**

38 One of the key questions for the application of MFD-based models is the calibration  
39 of the trip lengths. We start this section by briefly introducing the methodological  
40 framework (Sect. 2.1) proposed by Batista et al. (2018) and Batista et al. (2019)  
41 to calculate static trip length distributions considering the most detailed level of  
42 information. In Sect. 2.2, we discuss the extension of this methodological framework  
43 to determine time-varying trip length distributions.

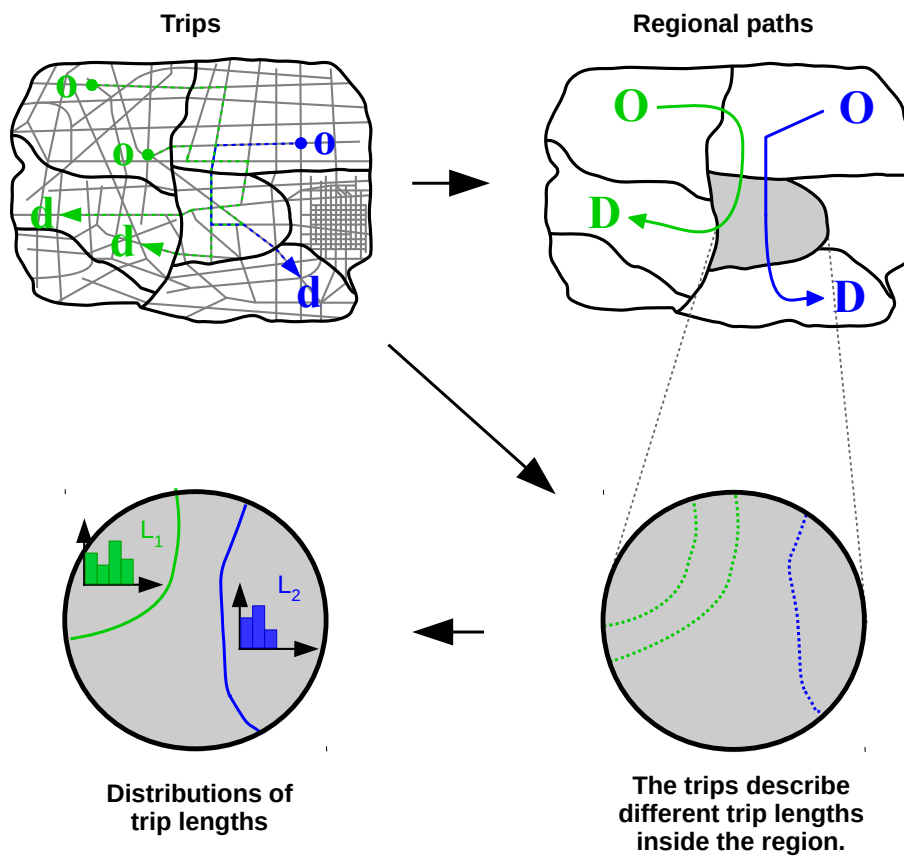


Fig. 2 – The scale up of trips into regional paths, that are characterized by trip length distributions.

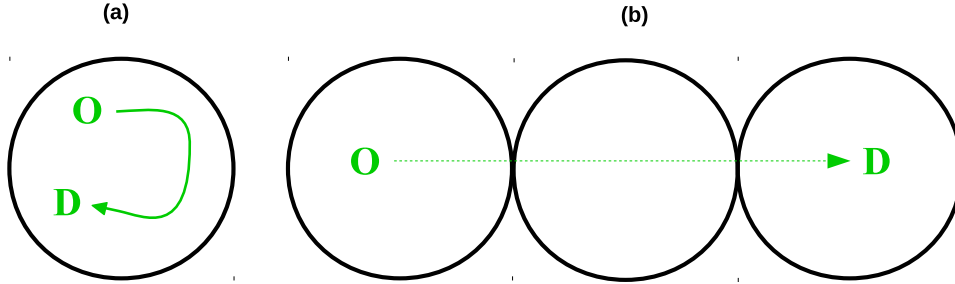


Fig. 3 – (a) *Internal path.* (b) *Regional path.*

## 2.1 Static trip length distributions

Batista et al. (2018) and Batista et al. (2019) proposed a methodological framework to explicitly calculate trip length distributions. The methodology utilizes a representative set of trips in the city network as well as its partitioning. Let  $G(N, A)$  be a graph that represents the city network, where  $N$  is the set of all nodes and  $A$  is the set of all links. To partition the city network, one can use one of the different techniques described in the literature (see e.g., Saeedmanesh & Geroliminis, 2016, 2017, Lopez et al., 2017, Casadei et al., 2018, Ambühl et al., 2019). Since the full set of true trips in the city network is not known and very difficult to estimate, the authors propose to construct a set of virtual trips by randomly sampling several origin-destination nodes in the city network and then calculate the shortest-path in distance for each pair. Let  $\Gamma$  be this set of virtual trips. The trip length distributions are determined based on four levels of information from the regional network. In this paper, we focus on the most detailed level that filters the virtual trips by their associated regional path. Generically, a regional path  $p$  is defined as:

$$p = (p_1, \dots, p_m, \dots, p_R), \forall m = 1, \dots, R \wedge m \in X \quad (2)$$

where  $R$  is the number of regions that define  $p$ .  $p_1$  and  $p_R$  are the Origin (O) and Destination (D) regions, respectively. In this paper, we distinguish between internal and regional paths (Batista & Leclercq, 2018). Figure 3 depicts these differences. A regional path crosses an ordered sequence of different regions. An internal path is defined by virtual trips that travel only within the same region.

The set of trip lengths  $L_r^p$  of regional path  $p$  in region  $r$  is (Batista et al., 2018, 2019):

$$L_r^p = \{\delta_{rk}^p l_{rk}\}, \forall k \in \Gamma \quad (3)$$

where  $l_{rk}$  is the length of virtual trip  $k$  that occurs in region  $r$ ; and  $\delta_{rk}^p$  is a binary variable that equals 1 if virtual trip  $k$  defines regional path  $p$ , or 0 otherwise.

The average trip length  $\bar{L}_r^p$  of regional path  $p$  in region  $r$  is:

$$\bar{L}_r^p = \frac{\sum_k \delta_{rk}^p l_{rk}}{\sum_k \delta_{rk}^p}, \forall k \in \Gamma \quad (4)$$

This level of information has two limitations (Batista et al., 2019). First, the average trip length  $\bar{L}_r^p$  (see Eq. 4) is strongly influenced when the set size  $L_r^p$  is small, i.e. there is a low number of virtual trips associated to the regional path  $p$ .

1 Let  $N_p$  be the number of virtual trips associated to regional path  $p$ . Second, the  
 2 trip length distributions for the Origin and Destination regions of regional path  $p$   
 3 depend on the spatial distribution of the sampled od pairs inside these regions.

## 4 2.2 Time-varying trip length distributions

5 The set of trip lengths  $L_r^p$  (see Eq. 3) is calculated from virtual trips that represent  
 6 shortest-paths in terms of distance, independent of the traffic conditions in the re-  
 7 gions. However, Yildirimoglu & Geroliminis (2014) showed that the trip lengths  
 8 depend on the traffic conditions and consequently change over time. In this pa-  
 9 per, we propose to extend the methodological framework described in the previous  
 10 section to calculate time-varying trip length distributions for MFD traffic models.  
 11 Generically, the set of trip lengths  $L_r^p$  depends on the traffic conditions:

$$L_r^p = f(v_1(n_1), \dots, v_m(n_m)), \forall m \in X \quad (5)$$

12 where  $v_m(n_m)$  is the speed-MFD that regulates the traffic conditions inside a generic  
 13 region  $m \in X$ . For a generic regional path  $p$ ,  $L_r^p$  is a multi-dimensional function  
 14 where the number of variables depend on the number of regions that define  $X$ , with  
 15 vehicles' accumulation  $n_m$ .

16 The speed-MFD of a region  $r \in X$  ranges between 0 and the free-flow speed  
 17  $v_r^{ff}(n_r)$ , i.e.  $v_r(n_r) \in [0, v_r^{ff}(n_r)]$ . The first step of the proposed extension consists  
 18 in building the multi-dimensional numerical grid, by discretizing the speed  $v_r(n_r)$   
 19 of each region  $r \in X$ :

$$\omega_r(n_r) = \{v_r^1(n_r), \dots, v_r^{N_r}(n_r)\}, \forall r \in X \quad (6)$$

20 where  $N_r$  is the total number of speed samples for region  $r$ ; and  $\omega_r(n_r)$  is the set  
 21 of discretized speeds for region  $r$ .

22 For each regional OD pair, we sample a set of origin and destination nodes in  
 23 the city network that are in the Origin and Destination regions, respectively. Note  
 24 that this set is fixed for each OD pair. Then, for each point of the multi-dimensional  
 25 numerical grid, we calculate the time-dependent shortest path connecting each od  
 26 pair in the city network using the classical Dijkstra algorithm. The travel time of  
 27 link  $a$  is:

$$t_a = \frac{l_a \delta_{ar}}{v_r^h(n_r)}, \forall a \in A \wedge \forall h = 1, \dots, N_r \quad (7)$$

28 where  $l_a$  is the length of link  $a$ ; and  $A$  is the set of links that define the city network.

29 We filter the time-dependent virtual trips following the regional path they  
 30 define and calculate the average trip lengths  $\bar{L}_r^p$  (see Eq. 4). Let  $\Omega^{OD}$  represent the  
 31 set of all regional paths gathered that connect the regional OD pair. This step allows  
 32 to determine the  $\bar{L}_r^p$  values in the multi-dimensional grid. There are two challenges  
 33 to implement this methodology. First, we need to sample a significant number of od  
 34 pairs in the city network for each regional OD pair. Second, the calculation of the  
 35 time-dependent virtual trips for each point in the multi-dimensional numerical grid  
 36 requires a large computational burden. To bypass these challenges, we make use of  
 37 the Latin hypercube technique (Tang, 1993) for sampling the od pairs. This allows  
 38 to gather a representative subset of all possible connections between the origin  
 39 and destination nodes. In one hand, using this approach significantly reduces the

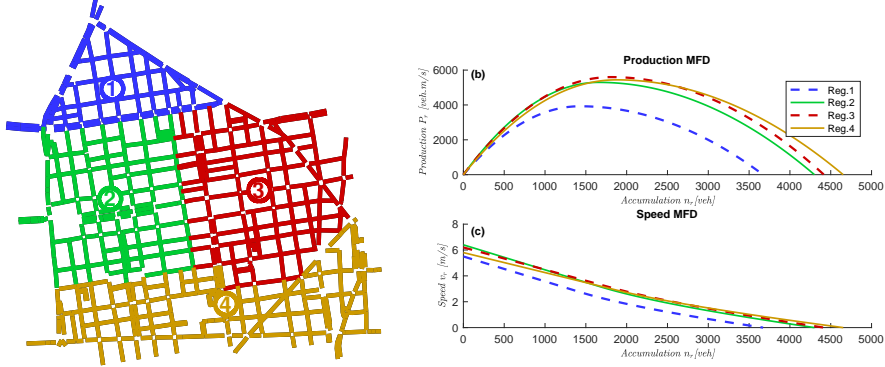


Fig. 4 – (a) 6<sup>th</sup> district Lyon network divided into four regions. (b) Production MFDs. (c) Speed-MFDs.

1 computational cost required. On the other hand, it also solves the question of the  
 2 sample size of od pairs we should consider, i.e. the number of od pairs that we  
 3 should sample to calculate the virtual trips set (Batista et al., 2019).

4 Suppose that  $\hat{L}_r^p$  is the average trip length that we aim to estimate given  
 5 a set  $v_r^*, \forall r \in X$  of average speeds in the regional network. That is  $\hat{L}_r^p =$   
 6  $f(v_1^*(n_1), \dots, v_m^*(n_m)), \forall m \in X$ . To estimate  $\hat{L}_r^p$ , we first find the location of  
 7  $v_r^*, \forall r \in X$  in the numerical grid  $\omega_r(n_r)$  (see Eq. 6). We then gather the  $2N_r$  close-  
 8 st points as well as the corresponding calculated average trip lengths  $\bar{L}_r^p$ . We fit a  
 9 multi-dimensional linear regression model defined as:

$$\bar{L}_r^p = \alpha_0 + \sum_{i \in X} \alpha_i v_i + \sum_{\substack{j \in X \\ i \neq j}} \alpha_{ij} v_i v_j, \forall r \in p \wedge \forall p \in \Omega^{OD} \quad (8)$$

10 where  $v_i$  are the predictors and represent the speed samples of region  $i$  previously  
 11 gathered from  $\omega_r(n_r)$ ;  $\alpha_0$ ,  $\alpha_i$  and  $\alpha_{ij}$  are the regression coefficients to be deter-  
 12 mined; and  $\Omega^{OD}$  is the set of all regional paths connecting the regional OD pair.

13 The average trip length  $\hat{L}_r^p$  is then estimatd as:

$$\hat{L}_r^p = \alpha_0 + \sum_{i \in X} \alpha_i v_i^* + \sum_{\substack{j \in X \\ i \neq j}} \alpha_{ij} v_i^* v_j^*, \forall r \in p \wedge \forall p \in \Omega^{OD} \quad (9)$$

### 14 3 Results and discussion

15 We now discuss the implementation of the methodological framework introduced in  
 16 the previous section. The test network is the 6<sup>th</sup> district of Lyon (France) depicted  
 17 in Fig. 4 (a). It is composed by 757 links and 431 nodes. This city network is  
 18 partitioned into four regions, for which we fitted the production-MFD and speed-  
 19 MFD functions depicted in Fig. 4 (b) and Fig. 4 (c), respectively. We assume a  
 20 bi-parabolic shape for the MFD (one parabola for the increasing and one for the  
 21 decreasing part of the MFD, with a first derivative equal to zero for the critical  
 22 accumulation that maximizes production). The free-flow speeds for regions 1 to 4  
 23 are  $v_1^{ff} = 5.2$  (m/s),  $v_2^{ff} = 6.4$  (m/s),  $v_3^{ff} = 6.2$  (m/s) and  $v_4^{ff} = 5.8$  (m/s).



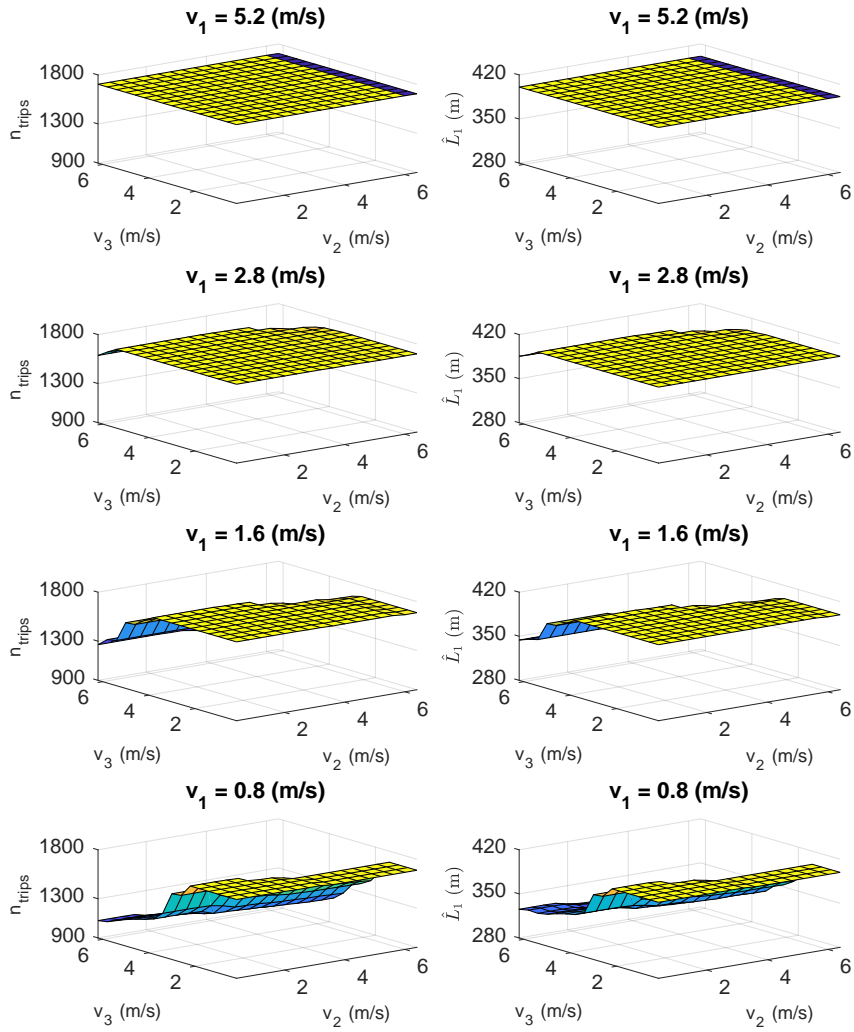


Fig. 5 – Left: Evolution of the number of time-dependent virtual trips  $N_p$  associated with regional path  $p = \{1\}$  as function of the speeds  $v_2$  and  $v_3$ . Right: same but for the average trip length  $\bar{L}_1$  (in m).

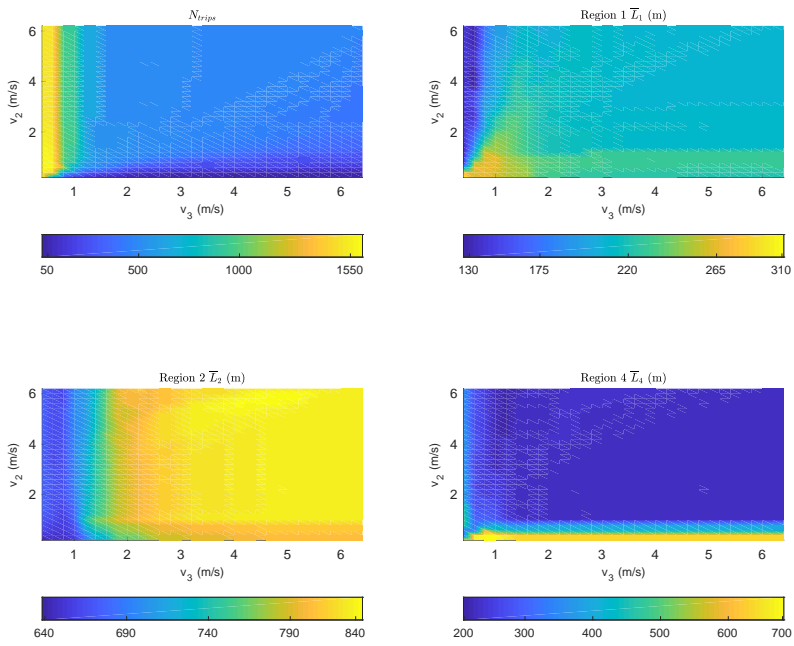


Fig. 6 – Evolution of the number of time-dependent virtual trips  $N_p$  associated with regional path  $p = \{124\}$  as well as of the average trip lengths (in m) for regions 1 ( $\bar{L}_1$ ), 2 ( $\bar{L}_2$ ) and 4 ( $\bar{L}_4$ ) as function of the speeds  $v_2$  and  $v_3$ .

1 We first analyze how the average trip lengths  $\bar{L}_r^p$  are influenced by the traffic  
2 states (i.e. their relation with the regional mean speeds  $v_r(n_r), \forall r \in X$ ) for an  
3 internal path  $p = \{1\}$  and a regional path  $p = \{124\}$ . To construct the multidimensional  
4 numerical grid, we discretize the speed-MFDs (see Fig. 4 (c)) of the four  
5 regions as  $\omega_1(n_1) \in [0.4 : \delta v : 5.2]$ ,  $\omega_2(n_2) \in [0.4 : \delta v : 6.4]$ ,  $\omega_3(n_3) \in [0.2 : \delta v : 6.2]$   
6 and  $\omega_4(n_4) \in [0.2 : \delta v : 5.8]$ , where  $\delta v = 0.4$  (m/s).

7 Fig. 5 depicts the evolution of the number of time-dependent virtual trips  
8 ( $N_p$ ) as well as of the average trip length  $\bar{L}_1^p = \{1\}$  as function of the speeds  $\bar{v}_2$   
9 and  $\bar{v}_3$ . We show the results for four values of  $\bar{v}_1 = 5.2, 2.8, 1.6, 0.8$  (m/s). We  
10 observe that under free-flow conditions of regions 1, 2 and 3, the number of time-  
11 dependent virtual trips that define regional path  $p = \{1\}$  is  $N_p \sim 1800$ . A similar  
12 trend is observed when the three regions are congested (i.e. when  $\bar{v}_1, \bar{v}_2$  and  $\bar{v}_3$   
13 are low). The average trip lengths  $\bar{L}_1$  are also not influenced by the traffic states  
14 because similar time-dependent virtual trips set are obtained for the previous two  
15 scenarios. As region 1 becomes more congested, while the adjacent regions 2 and  
16 3 are still in free-flow conditions, the number of time-dependent virtual trips  $N_p$   
17 associated with the internal path  $p = \{1\}$  decrease. For lower values of  $\bar{v}_1$ , the  
18 travel times of the city network links of region 1 increase. When the speeds in  
19 region 2 and 3 are in free-flow conditions, the city network links travel times for  
20 these two regions will be inferior than the ones of region 1. This means that the  
21 time-dependent virtual trips will detour to the links in regions 2 and 3 and then  
22 define other regional paths, such as for example  $p = \{1231\}$  and  $p = \{1321\}$ .  
23 The set of time-dependent virtual change and the average trip length  $\bar{L}_1^p = \{1\}$  is  
24 then dependent on the traffic conditions (i.e. on the observed mean speeds in the  
25 regions).

26 Fig. 6 also depicts the evolution of  $N_p$  as well as of the average trip lengths  
27 for regions 1 ( $\bar{L}_1$ ), 2 ( $\bar{L}_2$ ) and 4 ( $\bar{L}_4$ ) as function of  $\bar{v}_2$  and  $\bar{v}_3$ , for regional path  
28  $p = \{124\}$ . One can observe similar trends as in the case of regional path  $p = \{1\}$ .  
29 For low  $\bar{v}_2$  values, the link travel times of region 2 increase. When region 3 is  
30 in free-flow conditions, the time-dependent virtual trips detour from region 2 to  
31 3 and therefore define a different regional path  $p = \{134\}$ . This reduces the  $N_p$   
32 associated to regional path  $p = \{124\}$  and influences the average trip lengths. When  
33 both regions 2 and 3 are in free-flow conditions, the time-dependent virtual trips  
34 are more probable to cross the border of region 3 when their origin nodes are closer  
35 to this region. However, when  $\bar{v}_3$  is low, the travel times of the links in this region  
36 increase and the time-dependent virtual trips detour to region 2. This increases  
37 the average trip length in region 1 as observed in Fig. 6. This is also true for the  
38 destination region 4.

39 We also estimate the average trip lengths for regional paths  $p = \{1\}$  and  
40  $p = \{124\}$  (see Eq. 8 to Eq. 9), considering different set of  $\bar{v}_1, \bar{v}_2$  and  $\bar{v}_3$ . We  
41 have also determined the average trip lengths for these sets of speeds, based on the  
42 calculation of the time-varying virtual trips. The results are listed in Table 1 for  
43 regional path  $p\{1\}$  and in Table 2 for regional path  $p\{124\}$ . We observe that the  
44 estimated trip lengths show a good agreement with the calculated ones based on  
45 the time-varying virtual trips. The exceptions happen for regional path  $p\{124\}$  and  
46 low values of  $\bar{v}_2$  and  $\bar{v}_3$ , i.e. when the average trip lengths are more sensible to  $N_p$ .  
47 One solution is to consider a smaller  $\delta v$  to construct the numerical grid for smaller  
48  $\bar{v}_r, \forall r \in X$ .

$\bar{v}_1$	$\bar{v}_2$	$\bar{v}_3$	Region	
			1	
			$\bar{L}_1$	$\hat{L}_1$
5.10	0.60	1.15	407	407
2.50	5.80	6.13	369	369
3.40	2.15	4.36	407	407
4.33	3.77	5.20	407	407
1.05	5.40	2.40	324	320
0.66	0.50	5.95	406	403
0.45	0.60	0.88	407	397

Tab. 1 – Estimated  $\hat{L}_1$  and calculated average trip lengths  $\bar{L}_1$  (in m) for regional path  $p = \{1\}$  and different values of  $\bar{v}_1$ ,  $\bar{v}_2$  and  $\bar{v}_3$  (in m/s).

$\bar{v}_2$	$\bar{v}_3$	Region					
		1		2		4	
		$\bar{L}_1$	$\hat{L}_1$	$\bar{L}_2$	$\hat{L}_2$	$\bar{L}_4$	$\hat{L}_4$
0.60	1.15	200	270	666	652	298	679
5.80	6.13	208	209	833	821	225	229
2.15	4.36	214	226	801	809	232	228
3.77	5.20	210	214	828	813	225	230
5.40	2.40	209	231	827	754	229	229
0.50	5.95	134	225	674	792	354	632

Tab. 2 – Same as in Table 1, but for  $p = \{124\}$  and different values of  $\bar{v}_2$  and  $\bar{v}_3$ .

## 1 4 Outline

2 In this paper, we propose an extension of the methodological framework proposed  
3 by Batista et al. (2019) to determine time-varying trip lengths for the calibration  
4 of aggregated traffic models. We show how the traffic conditions in the regions  
5 influence the average trip lengths. We also show that the proposed methodology  
6 yields good estimation results for the average trip lengths. We plan to pursue this  
7 study for other regional paths and analyze the trip lengths estimation for larger  
8 city network partitioned into a larger number of regions.

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