

Trip lengths and the macroscopic traffic simulation: an interface between the microscopic and macroscopic networks

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1 Extended Abstract

2 Macroscopic traffic simulation has gained more and more interest from the scientific
3 community since the seminal works of Daganzo (2007) and Geroliminis & Daganzo
4 (2008). It assumes that traffic conditions are homogeneous inside a given region (or
5 reservoir); and traffic states are defined by a Macroscopic Fundamental Diagram
6 (MFD). Most implementations of MFD models are accumulation-based and have
7 been designed for control purposes. Few attention has been paid to the route choice
8 process, i.e. the characterization of most likely alternatives and calculation of path-
9 flow distribution. The most advanced MFD-based simulator including route choices
10 has been proposed by Yildirimoglu & Geroliminis (2014). The authors implemented
11 a multi-reservoir accumulation-based macroscopic traffic simulator. To calculate
12 the macroscopic routes and trip lengths, they considered the sampling of several
13 microscopic origin-destinations (OD) on the real network and made use of a time
14 dependent shortest-path algorithm. The route flows are assigned according to a
15 simple Multinomial Logit model. In fact, Multinomial Probit model has never
16 been implemented in such a framework, while lots of route correlations happen due
17 to the limited number of reservoirs used to describe an urban area. Furthermore,
18 the macroscopic route set definition still requires further investigations.

19 In this work, we propose to consider a multi-reservoir trip-based macroscopic
20 simulator (Mariotte et al., 2017) and further investigate the definition of (i) the set
21 of macroscopic routes between each OD pair; and (ii) the trip lengths of these routes.

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1 The route flow distributions are calculated based on time-dependent route costs and
 2 the Multinomial Probit model, that is solved using Monte Carlo simulations (Sheffi,
 3 1985). On the contrary of the accumulation-based macroscopic simulation, the trip-
 4 based model (Arnott, 2013, Mariotte et al., 2017) allows to easily consider different
 5 trip lengths for vehicles traveling inside the same reservoir. Arnott (2013) proposes
 6 to consider the evolution of the mean speed, $V(n(t))$, inside the reservoir. $n(t)$ is
 7 the accumulation inside the reservoir at time t , given by the MFD. The system
 8 dynamics can be entirely described by the vehicle trip length L :

$$L = \int_{t-T(t)}^t V(n(s)) ds \quad (1)$$

9 where $T(t)$ is the travel time of the vehicle exiting at t . Eq. 1 states that the trip
 10 length of a vehicle entering at $t - T(t)$ and exiting at t , corresponds to the integra-
 11 tion of the mean speed over this interval. Consequently, properly capturing these
 12 trip lengths is crucial for this simulation approach. Thus, we aim at investigat-
 13 ing the performance of two different approaches to calculate trip lengths per each
 14 macroscopic path (macro-path) p . Consider $p = \{i_1, \dots, i_j, \dots, i_N\}$ as the set of N
 15 reservoirs that compose macro-path p . The two approaches consist in calculating:

- 16 1. (method 1) a trip length distribution for each i -th reservoir (L_i). For this,
 17 we sample several microscopic ODs inside the i -th reservoir and calculate the
 18 shortest-path. The expected trip length for macro-path p and macroscopic
 19 OD is $E(L_p^{OD})$:

$$E(L_p^{OD}) = \sum_{j=1}^R \delta_j E(L_j) \quad (2)$$

20 where δ_j equals 1 if reservoir j belongs to macro-path p ; and R is the total
 21 number of reservoirs.

- 22 2. (method 2) a trip length distribution following the individual trajectories of
 23 vehicles inside each reservoir. The expected trip length $E(L_p^{OD})$ is decom-
 24 posed as:

$$E(L_p^{OD}) = E(L_{i_1/i_1 i_2}) + \sum_{j=2}^{N_1} E(L_{j/(j-1)j(j+1)}) + E(L_{i_N/i_{N-1}i_N}) \quad (3)$$

25 where $L_{i_1/i_1 i_2}$ is the distribution of trip lengths for people traveling from
 26 microscopic nodes inside i_1 to the border nodes with i_2 ; $L_{j/(j-1)j(j+1)}$ is the
 27 trip length distribution of people traveling on j , coming from $j - 1$ and going
 28 to $j + 1$; and $L_{i_N/i_{N-1}i_N}$ is the trip length distribution for travels between
 29 the border nodes with i_{N-1} and nodes inside i_N .

30 For this approach, we distinguish two ways of calculating $E(L_p^{OD})$:

- 31 (a) *Global procedure*, where we repeatedly sample several microscopic nodes
 32 inside i_1 and i_N and calculate the shortest-path, considering the whole
 33 microscopic network. We aggregate the paths according to the sequence
 34 of crossed reservoirs and their lengths are split according to the distri-
 35 butions of Eq. 3.

1 (b) *Local procedure*, where we repeatedly sample several microscopic origin
 2 nodes that are on the border between the (i_{j-1}, i) reservoirs and des-
 3 tination nodes that are on the border between the (i, i_{j+1}) reservoirs
 4 and calculate the shortest-path. For the origin (i_1) and destination
 5 (i_N) reservoirs of the macro-path p , we repeatedly sample several mi-
 6 croscopic internal and border nodes with the adjacent reservoirs i_2 and
 7 i_{N-1} ; and calculate the shortest-paths, respectively.

8 We note that to calculate the microscopic routes, it is also foreseen to con-
 9 sider route sampling techniques (e.g. Roberts & Kroese, 2007, Frejinger et al., 2009,
 10 Flotterod & Bierlaire, 2013).

11 To define the macroscopic route set, we consider the most likely paths ob-
 12 tained through trip length distributions obtained using a similar approach as pre-
 13 viously discussed (Method 2 - Global). To make the selection process independent
 14 of the traffic loading, at this step we consider distances and not travel-time.

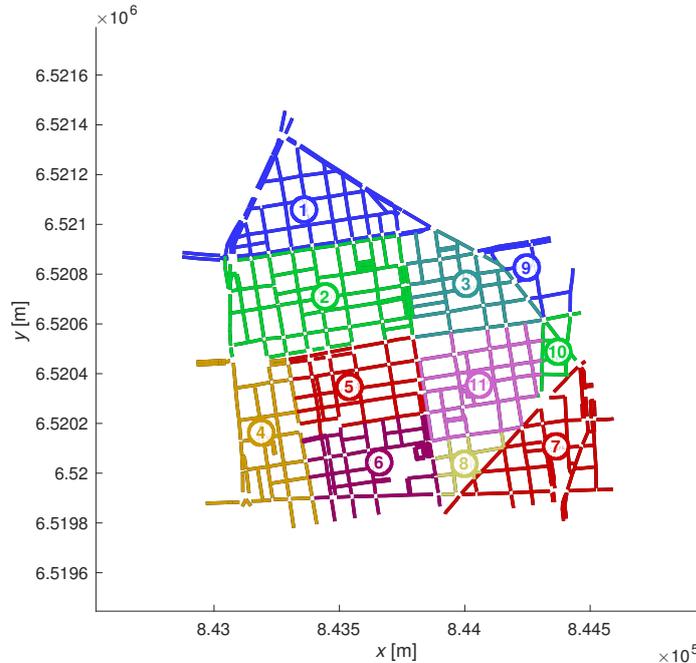


Fig. 1 – 6th district of Lyon divided into 11 reservoirs that are represented by the IRIS regions.

15 To show the applicability of our procedure, we highlight the first preliminary
 16 results obtained on the Lyon 6th district (Fig. 1), without the coupling with the trip-
 17 based simulator. We note that the large number of reservoirs is only for trip-length
 18 calculation tests. For macroscopic simulations, we may aggregate these regions into
 19 larger ones with a well defined MFD.

20 In Tab. 1, we show average and standard deviations of trip lengths for three
 21 macro-paths connecting reservoirs: 1 to 6; and 4 to 9. For all the calculations

1 of microscopic paths, we considered 1000 samples of origin and destination nodes.
 2 The microscopic routes were calculated using a shortest-path algorithm.

Macropath	<i>Method1</i>	<i>Method2 – Local</i>	<i>Method2 – Global</i>
(1,2,5,6)	1595±779	1889±672	1169±181
(1,2,5,11,6)	1945±956	2053±803	1219±213
(1,2,4,6)	1688±830	2196±696	1381±150
(4,5,2,3,9)	1796±895	1988±756	1440±212
(4,5,11,3,9)	1640±825	1940±567	1386±148
(4,6,8,7,10,9)	1725±904	2095±745	1586±130

Tab. 1 – Average and standard deviations for three macro-paths connecting reservoirs: 1 to 6; and 4 to 9. The trip lengths are listed in meters.

3 Our first results show that methods 1 and 2-Local give higher average trip
 4 lengths than method 2-Global. This may be due to the sampling of unrealistic
 5 paths inside the crossed reservoirs, which is also evidenced by the higher standard
 6 deviations.

7 The next step is to consider sampling techniques to calculate the microscopic
 8 routes; and analyze trip-based simulation results using the discussed approaches to
 9 calculate trip lengths.

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