Recent advances in multimodal MFD urban models

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Outline

• Macroscopic urban models
• New insights on multimodal MFD from the pNEUMA experiment
• The existing formulations for MFD models
• Multi-reservoir systems and traffic assignment
• Applications of NMFD approaches
  – Large-scale simulation of Lyon Metropolis
  – Overall assessment of a ride-sharing system
  – An optimal route guidance strategy based on avoidance maps
  – Trip length calibration and perimeter control
Introduction to macroscopic urban models
Transportation models

Local traffic dynamics
Open simulation platform (Symuvia)
(Leclercq et al, 2009-2015)

Static model for planning
Room for large-scale dynamic models

4
Large-scale dynamic urban simulation (1)
Large-scale dynamic urban simulation (2)
MFD definition

FD + Network structure (topology / signal timings) + Route choices = MFD
Multimodal MFD extension
New insights on multimodal MFD from the pNEUMA experiment

Experimental setting

https://open-traffic.epfl.ch/
Ideal for multimodal research

- Cars
- Taxis
- Buses
- PTWs
- Medium and Heavy Vehicles

TEN DRONES
Hovering simultaneously over different areas

5 DAYS
Monday to Friday

MASSIVE URBAN TRAJECTORY DATASET
More than 0.5 million trajectories

OPEN ACCESS
Free distribution. No barriers.

MORNING PEAK-HOUR
Five flight sessions for 2.5 hours per day

100+ INTERSECTIONS
Signalised or not

GLOBAL IMPACT
Made for researchers around the world

PERFECT FOR PHD
Stop searching for data and start your analyses!

Barbounakis and Geroliminis, 2020, part-C
2D MFD

Figure 1: Athens network: map of the area and its link level description. (a) Map of Athens, Greece ©OpenStreetMap 2020. (b) Link level representation of Athens. Links in blue are present inside the considered area.

Figure 2: 2D MFDs of considered region. (a) Production MFD. (b) Mean speed MFD.

namely October 19, 2018, October 24, 2018, October 29, 2018, October 30, 2018 and November 1, 2018. In the present work, only data from the last four days of the experiment is used. On the first day, the morning peak hour from 08:30 AM to 11:00 AM was monitored, whereas on the remaining three days, the traffic stream from 08:00 AM to 10:30 AM was monitored. The video recordings were processed to extract the individual trajectories of each vehicle along with its mode. In the current dataset, six different modes are identified: private cars, taxis, buses, medium vehicles, heavy vehicles, and PTWs. Although the raw data has a higher sampling frequency of 0.04 s, for the current study, it is eventually downgraded to 1 s in order to ease the data processing. More details about the experimental setup can be found in Barmpounakis and Geroliminis (2020) and hence, they are omitted here.

Since the drones have a limited battery life, the recordings were intermittent. Drones were brought back to change the batteries and thus, 12 min to 15 min of recording was lost inside each 30 min period. Hence, for every 30 min period the active recording time is only around 15 min to 17 min. It is noticed that not all drones were recording either at the beginning or towards the end of active recording periods due to synchronization issues. Only data corresponding to complete drone coverage is considered to minimize the bias in estimating macroscopic variables in the current work. According to the...
Unimodal speed regression

Also considered where the mean speed of a given mode is assumed to depend on that mode only, it is possible to quantify the relative importance of all modes on the mean speed of each mode. Besides, unimodal approach is limited for estimating the negative effect of mode presence. Where accurate traffic state estimation is required, a linear functional form assumed in the present work can be expressed as follow, if the data across the wider ranges of accumulation is available, it is necessary to consider a piece-wise linear functional form to approximate the mean speed of each mode.

In the current work mean speed of each mode is assumed to be a function of accumulation. Thus, in the current work mean speed of each mode is assumed to be a function of accumulation. However, it was impractical to estimate the bi-modal MFDs in the current analysis due to the sample size.

### Appendix A

<table>
<thead>
<tr>
<th>Car mean speed, $v_c$ (ms$^{-1}$)</th>
<th>Car accumulation, $n_c$ (veh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Taxi mean speed, $v_t$ (ms$^{-1}$)</td>
<td>Taxi accumulation, $n_t$ (veh)</td>
</tr>
<tr>
<td>Bus mean speed, $v_b$ (ms$^{-1}$)</td>
<td>Bus accumulation, $n_b$ (veh)</td>
</tr>
<tr>
<td>MV mean speed, $v_{MV}$ (ms$^{-1}$)</td>
<td>MV accumulation, $n_{MV}$ (veh)</td>
</tr>
<tr>
<td>HV mean speed, $v_{HV}$ (ms$^{-1}$)</td>
<td>HV accumulation, $n_{HV}$ (veh)</td>
</tr>
<tr>
<td>PTW mean speed, $v_{PTW}$ (ms$^{-1}$)</td>
<td>PTW accumulation, $n_{PTW}$ (veh)</td>
</tr>
</tbody>
</table>

The linear functional form assumed in the present work can be expressed as follow.

\[
\begin{align*}
\hat{v}_i &= \sum_{j=1}^{M} a_j v_j + b_i \\
\end{align*}
\]

Where $a_j$ represents the regression coefficient, $v_j$ is the mean speed of mode $j$, and $b_i$ represents the intercept. This functional form has a clear physical meaning and it is suitable for traffic state estimation.
Multimodal speed regression

\[ v_j = v_{f,j} + \alpha_{c,j} n_c + \alpha_{t,j} n_t + \alpha_{b,j} n_b + \alpha_{m,j} n_m + \alpha_{p,j} n_p, \quad \forall j = \{c,t,b,m,p\}, \]

(a) Car regression coefficients, \( \alpha_{c,j} \)

(b) Taxi regression coefficients, \( \alpha_{t,j} \)

(c) Bus regression coefficients, \( \alpha_{b,j} \)

(d) MV regression coefficients, \( \alpha_{m,j} \)

(e) PTW regression coefficients, \( \alpha_{p,j} \)
Comparison uni vs. multi regression

<table>
<thead>
<tr>
<th>Mode</th>
<th>p-values</th>
<th>( v_{f,j} )</th>
<th>( R^2 )</th>
<th>RMSRE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Uni-</td>
<td>Multi-</td>
<td>Uni-</td>
<td>Multi-</td>
</tr>
<tr>
<td>Car</td>
<td>0.01</td>
<td>0.01</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Taxi</td>
<td>0</td>
<td>0.80</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bus</td>
<td>0</td>
<td>0.14</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>MV</td>
<td>0</td>
<td>0.01</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>PTW</td>
<td>0</td>
<td>0</td>
<td>0.06</td>
<td>0</td>
</tr>
</tbody>
</table>

The table above presents the statistical p-values, mean speed in ms, \( R^2 \), and RMSRE values of uni- and multi-modal mean speed fits for all modes using NNLS method. This shows the importance of a multi-modal approach in improving the accuracy of mean speed estimation, especially for cars, taxis, and medium vehicles. The multi-modal mean speed MFD captures the variation of mean speed over the uni-modal counterpart, indicating significant improvements for some modes. However, data coverage remains a limitation for the current analysis.
The multimodal two-fluid model

Running speed
\[ v_r = v_{f,r} (f_r)^{\tilde{n}} \equiv v_{f,r} (1 - f_s)^{\tilde{n}}, \]

Mean speed
\[ v = v_{f,r} (f_r)^{\tilde{n}+1} \equiv v_{f,r} (1 - f_s)^{\tilde{n}+1}. \]

Fraction of vehicles that are stopped during a given time interval, i.e.,

\[ f_s = \frac{T_s}{T}, \]

(Herman and Prigogine, 1979)

The multimodal counterpart

\[ v_{r,j} = v_{f,r,j} \prod_{k \in \mathcal{M}} (1 - f_{s,k})^{\tilde{n}_{k,j}}, \quad \forall j \in \mathcal{M} \quad \text{and} \quad \mathcal{M} = \{c,t,b,m,p\}, \]

\[ v_j = v_{f,r,j} (1 - f_{s,j}) \prod_{k \in \mathcal{M}} (1 - f_{s,k})^{\tilde{n}_{k,j}}, \quad \forall j \in \mathcal{M} \quad \text{and} \quad \mathcal{M} = \{c,t,b,m,p\}. \]
The Uni two-fluid model

(a) Car trip time, \( T_c \) vs. Car stopped time, \( T_{s,c} \)

(b) Taxi trip time, \( T_t \) vs. Taxi stopped time, \( T_{s,t} \)

(c) Bus trip time, \( T_p \) vs. Bus stopped time, \( T_{s,b} \)

(d) MV trip time, \( T_{m} \) vs. MV stopped time, \( T_{s,m} \)

(e) PTW trip time, \( T_{p} \) vs. PTW stopped time, \( T_{s,p} \)
The Multi two-fluid model

Figure 7: Comparison of empirical data and model results between stopped time and total time per unit distance in the multi-modal two-fluid regression for all modes considered. (a) Car. (b) Taxi. (c) Bus. (d) Medium Vehicle (MV). (e) PTW.
Estimating $f_s$ - ergodicity assumption

Weak ergodicity (based on probe sampling) \[ \hat{f}_s = \frac{T_s}{T}, \]

Strong ergodicity (based on probe sampling) \[ \hat{f}_s = \left\langle \frac{T_s}{T} \right\rangle. \] (Ardekani, 1984)
The existing formulations for MFD models


The single reservoir setting

Classical dynamic approach

Reservoir (NMFD) approach

Uniform outflow

Uniform accumulation

Uniform inflow
The accumulation-based (bathtub) model

\[ \frac{dn(t)}{dt} = q_{in}(t) - q_{out}(t) \]

The outflow-MFD is hard to calibrate in practice; this is why the steady-state approximation is used.

\[ q_{out}(t) = \frac{Q(n(t))}{L_{trip}} \]
Wave propagation in a single reservoir

First illustration of the causality effect
Trip-based model

Model formulation

\[ \int_{t-T(N_{out}(t))}^{t} V(n(s)) ds = L \]  
(Arnott, 2013)

\[ T(N_{out}(t)): \text{experimented travel time for vehicle } N_{out} \text{ that exits at time } t \]

\[ Q_{out}(t) = \frac{Q_{in}\left(t-T\left(N_{out}(t)\right)\right)V(n(t))}{V\left(n\left(t-T\left(N_{out}(t)\right)\right)\right)} \]

(Delay differential equation with endogenous delay)

\[ Q_{out}(t) = Q_{in}(t) + n'(t) \]

(Accumulation-based MNFD model)

Analytical resolution (piecewise cst inflows)

Model solutions
Trip-based model (2)

Advantages

- Direct access to entry and exit times for all individual vehicles
- Efficient numerical scheme as only the next vehicle to exit should be updated in practice at each event
- Straightforward extension to account for heterogeneous travel distances

\[ t_{\text{out}}(4) = \frac{L}{V(n_1)} \]

An event-based numerical scheme

(Leclercq et al, TRptB, 2017)
Multimodal extensions

- **Accumulation-based version**

\[
\frac{dn_i(t)}{dt} = q_{\text{in},i}(t) - q_{\text{out},i}(t) \quad \text{with} \quad q_{\text{out},i}(t) = \frac{n_i \ P(n_i \ldots)}{n} \ L_i
\]

- **Trip-based version**

\[
L_{c,r} = \int_{t-\tau_{c,r}(t)}^{t} v_{c,r}(n_{c,r}(s), n_{p,r}(s)) \ ds,
\]

- **Accumulation-based version with delay**

\[
\int_{-\infty}^{t} q_{m,\text{in}}(s) \ ds = \int_{-\infty}^{t+\tau_{m}(t)} q_{m,\text{out}}(s) \ ds.
\]

\[
q_{m,\text{out}}(t + \tau_{m}(t)) = \frac{q_{m,\text{in}}(t)}{1 + \frac{d\tau_{m}(t)}{dt}}.
\]

It requires stabilization when inflow decreases

Comparison of multimodal MFD extensions

Motivation

Multimodal MFD-based models

Numerical Results

Conclusions

Acknowledgments

References

Verification with micro-simulation

Shared bus lane

Bus stop

Dedicated bus lane

Single 3D MFD

As discussed earlier, this total production is split into partial productions based on the partial accumulation values in the MFD-based modeling. In the present case, the demand for buses is very small compared to cars, which results in a smaller accumulation of buses compared to cars and hence, smaller partial production. This can drive the solution into a different equilibrium state on the 3D-MFD plane.

Now, the same scenario is considered with two segregated 3D-MFDs instead of a single aggregated 3D-MFD in order to verify if separating the 3D-MFD can result in accurate solutions.

Fig. 16 presents the evolution of accumulation, outflow and mode share for the same scenario considered before, but using two segregated 3D-MFDs. The notable observation compared to previous results is that all MFD-based models reach the same steady state as micro-simulation.

It is clear from the evolution of accumulation plots in Fig. 16a and b. Analyzing the transition period in the accumulation evolution plots, it is clear that the conclusions made in previous test cases hold true.

Similarly, the outflow evolutions of MFD-based models follow the micro-simulation ones. The delay in the outflow increase (or decrease) to the increase (or decrease) in demand can be clearly noticed in the delay accumulation-based and the trip-based models, where the results of stated MFD-based models are in very good agreement with the micro-simulation.

The outflow decrease for cars during demand drop in the micro-simulation is little diffusive owing to the aggregation process.
Segragated 3D MFD

(a) Accumulation vs. time for cars.

(b) Accumulation vs. time for buses.

(c) Outflow vs. time for cars.

(d) Outflow vs. time for buses.
Multi-reservoir systems and traffic assignment


Multi-reservoir systems

Real network

Clusters with well-defined MFDs

Routing

Simulation

A crucial question: trip lengths estimation

Flow exchanges
Estimation of the trip lengths

4 methods based on a single local od trip sampling (10000) and then aggregation

Current reservoir (M1)

Current and next reservoirs (M2)

Current, previous and next reservoirs (M3)

Macro-routes (M4)

(Batista et al., 2018)
Impacts on the simulation results

Time-evolution of the accumulation
Trip lengths estimation - cellphone data

LBS data over Dallas city (US) – 6 months

Detour ratio ($d_R$)

Normalised mean speed ($\bar{v}$)

Trip length dynamics

Application to the Lyon Metropolis


MFDUrbaSim (A python open-source MFD simulator): https://github.com/licit-lab/MFDurbanSim
2.2. Simulation of traffic states for the Lyon metropolitan area (France)

The urban area inside the first ring road of Lyon consists of 27,000 links with an area of 170 km$^2$ and where around 1 million trips are recorded each day. The network configuration with its environment is given in Figure 2.5. This area exchanges traffic with its surroundings via mainly 4 freeways related to 4 origin/destination cities as presented in Figure 2.5: freeway A6 from/to Paris, freeway A42 from/to Geneva, freeway A43 from/to Grenoble and freeway A7 from/to Marseille.

The available network data includes the number of lanes and the signal settings at each node with traffic lights. As mentioned in section ..., this can help to determine some characteristic values for the MFD estimation.

Demand data

The demand was estimated for a typical weekday in a preliminary study from J. Krug and A. Burianne, engineers members of the MAGnUM project. Their study uses a four-step model based on household trip surveys and socio-demographic data to improve the localization of trip origins and destinations. The estimated OD matrix is defined for each hour of the day at the level of IRIS urban areas, the French partitioning system for demographical data. The spatial extension of an IRIS area may thus vary as its definition is based on a fixed range of inhabitants, workers, etc. In the network studied, each IRIS area comprises around 2000 inhabitants and may extend from 0.5 to 2 km$^2$. The OD matrix also includes the demand for trips from and to outside the perimeter of interest.

For this first application example, the network will be clustered into reservoirs by aggregating several neighboring IRIS areas together (demand-oriented clustering). The total demand is divided into single reservoirs, 5-reservoirs, and 10-reservoirs.
Demand estimation

Demographical partitioning of Lyon (IRIS zones)

The OD matrix at the level of IRIS zones comes from Lyon authorities (Household survey 2015)
The 1-reservoir case

MFD calibration

Simulation results
The 5-reservoir case – user equilibrium

Gap = 4.9
3 % of OD with a Gap\textsubscript{od} > 0.2
The 5-reservoir case – best fit

Gap = 5.4
7 % of OD with a Gap^{od} > 0.2
The 10-reservoir case – best fit

Gap = 61
31 % of OD with a Gap$^{od}$ > 0.2
Assessing ride-sharing services

Test Case – Northern Lyon

Test cases
Lyon 6 + Villeurbanne

Scale of 25 km²
62450 requests
11235 Service requests
1,883 nodes and 3383 links
6:30 to 10:30 AM (morning peak)
Rolling horizon: 20 min
Optimization time step: 10 min
Test case – Full Lyon

Test cases
Lyon

Scale of 80 km²
484,690 requests
205,308 Service requests
11,314 origin/destination set points
6 to 10 AM (morning peak)
Rolling horizon: 20 min
Optimization time step: 10 min
Traffic dynamics for different market share

Traffic situation for the number of sharing 0 with different market-shares

Increase in travel time

Market-share 100%: 5.5%
Market-share 80%: 4.4%
Market-share 60%: 3.3%
Market-share 40%: 2.3%
Market-share 20%: 1.1%
Traffic dynamics for different sharing level

Northern Lyon

Market-share = 100%

Accumulation vs. Time (100 s)

- Blue: Market-share = 0
- Orange: nshare = 0
- Pink: nshare = 1
- Green: nshare = 2
Application to full Lyon Metropolis (1)
Chapter 6. Transportation Analyses

Figure 6.16 and figure 6.17 show the total travel time and distance for all the service and personal cars in the network for different market-shares when the number of sharing is 0, 1, and 2. It is clear that with the number of sharing zero, total travel time and distance increases with increasing the market-share. Market-share = 100% with the number of sharing zero can increase the total travel time by 5.6% and the total travel distance by 3.7%. Then, sharing can fix this problem by reducing the total travel time by 30.0% with the number of sharing 1 and 41.1% with the number of sharing 2 compared to the number of sharing 0. Furthermore, the total travel distance is reduced by 25.5% with the number of sharing 1 and 36.0% with the number of sharing 2.

6.2.4 Number of sharing

![Graph showing the total travel time and distance for different market-shares and numbers of sharing.](image-url)

Full Lyon
<table>
<thead>
<tr>
<th>Number of sharing</th>
<th>Number of trips</th>
<th>Number of cars</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>205124</td>
<td>17102</td>
</tr>
<tr>
<td>1</td>
<td>105745</td>
<td>9489</td>
</tr>
<tr>
<td>2</td>
<td>72160</td>
<td>6826</td>
</tr>
<tr>
<td>3</td>
<td>69790</td>
<td>6595</td>
</tr>
</tbody>
</table>
Impact of dynamic ride-sharing on large-scale network
Market-share

Total travel distance for all the cars for the number of sharing 0, 1 and 2 with different market-shares

3.7%
-25.5%
-36.0%
### Impact of dynamic ride-sharing on large-scale network

#### Capacity of vehicles
- Regular vehicle: capacity = 4, nshare = 3
- Big vehicle: capacity = 6, nshare = 5
- Van-pooling: capacity = 10, nshare = 9
- Shuttle-sharing: capacity = 20, nshare = 19

<table>
<thead>
<tr>
<th>Configuration</th>
<th>Shared vehicles</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>Number of trips</td>
</tr>
<tr>
<td>MS: 100%</td>
<td>69790</td>
</tr>
<tr>
<td>Capacity = 4</td>
<td>63304</td>
</tr>
<tr>
<td>Capacity = 6</td>
<td>46448</td>
</tr>
<tr>
<td>Capacity = 10</td>
<td>30004</td>
</tr>
</tbody>
</table>

**Traffic situation for different vehicle capacity (market-share = 100%)**
An optimal route guidance strategy based on avoidance maps

Route guidance based on avoidance maps
Assessment on a toy network

Manhattan network

45% rerouted vehicles
7.4% mean increase in distance

Control efficiency
Assessment on a real network

Northern Lyon network

ERC PoC MAGnUM+ (prototype and first field tests)
Special thanks to the MAGnUM team!
Thank you for your attention