KU Leuven Mobility Research Centre – CIB: traffic research

prof.dr.ir. Chris Tampère
L-Mob KU Leuven mobility research centre
master ir. Logistics & Traffic KU Leuven
Who am I?

• 1997-2004: TNO Inro, Delft (commercial) research projects on traffic data, ADAS simulation, ITS, transportation modeling

• 1999-2004: TU Delft, PhD on traffic flow theory with ADAS and human factors. Supervision: Henk van Zuylen, Bart van Arem, Serge Hoogendoorn

• 2003-now: KU Leuven postdoc, later professor (2010) dynamic network traffic modeling, network traffic control and pricing, mobility behavioral modeling, traffic and tracking data,…

• 2011-now: educating engineers in Logistics & Traffic
Network traffic modeling and simulation

Link Transmission Model
Link Transmission Model

- Continuum traffic modeling = traffic as a fluid
- Dynamic Network Loading
  - Dynamic propagation over links and nodes
  - Spillback, intersections
- Dynamic User Equilibrium/Traffic Assignment
  - Dynamic shortest path
  - Equilibrium route choice modeling
- Efficient algorithms
  - Arbitrarity long time step (no CFL)
  - Warm start/marginal computation

Animation of vehicle density during peak period R0-E40-E314

Density space time plots with varying time resolution in peak on R0-E40-E314

Animation of accessibility during peak period Rotterdam centre
Grid with interpolation & implicit algorithm (no CFL)

Iterate each (larger) time step until convergence

Warm start: initial guess from previous (nearby) simulation

MaC: at each iteration, only recompute grid points whose precedents changed significantly in previous iteration (NB: in smart order, because Gauss-Seidel)

## Test Networks

<table>
<thead>
<tr>
<th>Network</th>
<th>size</th>
<th>#Nodes</th>
<th>#Links</th>
<th>#OD’s</th>
<th>#Dest</th>
<th>Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>R0-E40-E314</td>
<td>43.4km</td>
<td>39</td>
<td>60</td>
<td>42</td>
<td>9</td>
<td>4h</td>
</tr>
<tr>
<td>Rotterdam</td>
<td>599.6km</td>
<td>331</td>
<td>562</td>
<td>1890</td>
<td>44</td>
<td>4h</td>
</tr>
<tr>
<td>Regional The Hague</td>
<td>1704.1km</td>
<td>1636</td>
<td>3722</td>
<td>13603</td>
<td>160</td>
<td>4h</td>
</tr>
<tr>
<td>Regional Leuven</td>
<td>2201.5km</td>
<td>2581</td>
<td>4653</td>
<td>52441</td>
<td>417</td>
<td>4h</td>
</tr>
</tbody>
</table>

![Network Diagrams](image-url)
## Overview Performance

<table>
<thead>
<tr>
<th>Network</th>
<th>#size</th>
<th>#Nodes</th>
<th>#Links</th>
<th>#OD’s</th>
<th>#Dest</th>
<th>#Period</th>
<th>Potential for repeated DNL</th>
</tr>
</thead>
<tbody>
<tr>
<td>R0-E40-E314</td>
<td>43.4km</td>
<td>39</td>
<td>60</td>
<td>42</td>
<td>9</td>
<td>4h</td>
<td>~10x</td>
</tr>
<tr>
<td>Rotterdam</td>
<td>599.6km</td>
<td>331</td>
<td>562</td>
<td>1890</td>
<td>44</td>
<td>4h</td>
<td>~100x</td>
</tr>
<tr>
<td>Regional The Hague</td>
<td>1704.1km</td>
<td>1636</td>
<td>3722</td>
<td>13603</td>
<td>160</td>
<td>4h</td>
<td>~300x</td>
</tr>
<tr>
<td>Regional Leuven</td>
<td>2201.5km</td>
<td>2581</td>
<td>4653</td>
<td>52441</td>
<td>417</td>
<td>4h</td>
<td>~700x</td>
</tr>
</tbody>
</table>

Density space time plots with varying time resolution in peak on R0-E40-E314

Total computation time (s)

Time interval (min)
Current case study

- 1314 zones
- 12670 nodes, (710 signals)
- 29062 links
Codes are available

- Matlab Toolbox for Dynamic Traffic Assignments
- Also: Github, Matlab central

In conjunction with the 6th Symposium on Dynamic Traffic Assignment, and with TRAF’s Traffic Flow Theory and Characteristics 2016 Summer Meeting, the KU Leuven Mobility Research Centre is pleased to invite you to

**The first open Link Transmission Model Workshop:** ‘Hands on experience with LTM’

The workshop will take place on **Friday July 1, 2016** from 9.30 am in the Computer lab, Cadington Building (H69) on Cadington St, Darlington Sydney

Please register (free of charge) before **June 1st, 2016** via [www.mech.kuleuven.be/ltm-registration](http://www.mech.kuleuven.be/ltm-registration)


Network traffic modeling and simulation: Current developments

• Hybrid network modeling
  o multiclass traffic
    • e.g.: public transit vehicles, AV’s, city logistics vehicles
    • each simulated with own propagation logic
      • micro or macro
    • on mixed and shared infrastructures
    • iterative consistency algorithms
      • inheriting warm start and marginal computation capabilities of i-LTM
  o alternative intersection models
    • queuing theory
    • scheduling of co-operative vehicles
    • micro/meso propagation over nodes
Network traffic modeling and simulation: Current developments

• Equilibrium modeling
  o sequential DTA equilibration
  o stochastic route choice with full route enumeration
  o departure time modeling: efficient algorithms
  o equilibration in non-separable systems
• DTA as interoperable tool
  o consistency framework and algorithms across multiple models
    • e.g.: disaggregate demand model, spatial model,…
  o through ‘death reckoning’ (local model approximations and sequential updating)
Anticipatory network traffic control

bi-level DNL and DTA problems
Problem description – achievements

• Optimization, s.t. DNL/DTA constraints
  - e.g. pricing, traffic signals, calibration,…

• Exploiting the warm-started, efficient LTM network loading/assignment algorithm

• Decomposition of anticipatory network traffic control
  - Static assignment
    - algorithms for fully decomposed (controller-wise) control
  - Dynamic assignment
    - fully decomposed control
    - dynamic behavioural clustering

• Iterative Learning Control
  - daily repetition allows correcting model approximation errors for route choice response anticipation
Anticipatory Model Predictive Control (online) / optimal network control planning/calibration (offline)

\[
\min_{g_m} \tilde{J}_{TTS} = \min_{g_m} \tilde{J}_{TTS}(\hat{n}_{u,d}(k_s), g_m(k_s))
\]

\text{s.t. } \hat{n}_{u,d}(k_s) = f(\hat{n}_{u,d}(k_s - 1), g_m(k_c), \hat{d});
\]
\[g_{m,min} \leq g_m(k_c) \leq g_{m,max} \forall m \in M;\]

With \( f(\cdot) \) the Dynamic User Equilibrium
Example: Model predictive control (online - rolling horizon)

Test network

O/D Demand

<table>
<thead>
<tr>
<th>O-D Node</th>
<th>Demand</th>
<th>0/0</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1750/3500</td>
<td>0/0</td>
</tr>
<tr>
<td>10</td>
<td>1250/2500</td>
<td>0/0</td>
</tr>
<tr>
<td>13</td>
<td>0/0</td>
<td>1000/2000</td>
</tr>
</tbody>
</table>
Non Convex Example:

\[ c_l(f_l) = 1 + \alpha_l \left( \frac{f_l}{400} \right)^{\beta_l} \]

Not easily tackled analytically

<table>
<thead>
<tr>
<th>Link</th>
<th>( \alpha_{10} )</th>
<th>( \beta_{10} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Link 10</td>
<td>0.3</td>
<td>4</td>
</tr>
<tr>
<td>Link 11</td>
<td>0.2</td>
<td>2</td>
</tr>
<tr>
<td>Link 12</td>
<td>0.5</td>
<td>2</td>
</tr>
<tr>
<td>Link 13</td>
<td>0.2</td>
<td>4</td>
</tr>
</tbody>
</table>
Non Convex Example: initial point matters
A sensitivity-based clustering approach for adaptive decomposition of anticipatory network traffic control
Iterative learning of model error

\[ f^E(q, \mu) \]

Reality

Model

\[ (g_k^*, f_k^{\text{real}}) \]

\[ (g_{k+1}^*, f_{k+1}^{\text{real}}) \]

\[ (g_{k+2}^*, f_{k+2}^{\text{real}}) \]

\[ (g_{\text{real}^*}, f_{\text{real}^*}) \]

\[ (g_k^*, f_k^*) \]
Publications bi-level control


Publications DTA calibration


Strategic Multimodal Model

Mobility portfolio choice based on multi-day trip patterns
Not all modal decisions done at the same time

Short-term
Standard Planning Tools

Medium-term

Long-term

Strategic Planning Tools
Problem description – achievements

• Most transportation models = 1 peak or day
  o traditional 4-stage planning models
  o activity-based models
• = insufficient to explain modal choice, as people prefer one-fits-all solution packages

• Important when predicting adoption of new mobility options
  o electric bicycle, car sharing, Mobility as a Service (MaaS)
• Exploration of multi-day trip patterns as predictors of mobility portfolio
  o joint choice model on trip set
  o data statistical matching techniques
Strategic Multimodal Model: achievements

1. How to predict mobility resource ownership decisions?
2. How to find and describe important determinants?
3. Where to get the data?
4. How to frame the mobility ownership model into more complex modeling structures?
Strategic demand model: joint choice model of portfolio on trip set

- Multiple day travel observations
- Mobility resource ownership
- Supply characteristics

**Mobility resource ownership model**

\[
U_d^i = V_{d,\text{non-travel}} + V_{d,\text{travel}} + \epsilon_d
\]

- Mobility market shares forecasting
- Travel behavior analysis (i.e. model parameter coefficients)
- Sensitivity analysis to supply and external changes
\[ U_d^i = V_d^{i,\text{non-travel}} + V_d^{i,\text{travel}} + \varepsilon_d^i \]

### Simulation

- Observed market shares
- Simulated market shares

<table>
<thead>
<tr>
<th>Observed</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>RCS_C</td>
<td>83.2</td>
</tr>
<tr>
<td>RCS_CB</td>
<td>52.9</td>
</tr>
<tr>
<td>RCS_CP</td>
<td>9.2</td>
</tr>
<tr>
<td>RCS_CBP</td>
<td>3.3</td>
</tr>
<tr>
<td>SUM (predict.)</td>
<td>148.7</td>
</tr>
</tbody>
</table>

### Forecasting

- tt50: PT travel times reduced by half
- tt50: PT travel times doubled
- FC50: bicycle fixed cost reduced by half
- FC200: bicycle fixed cost doubled

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Differences [-]</th>
<th>Differences [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RCS_C</td>
<td>RCS_CB</td>
</tr>
<tr>
<td>Simulation - Observed</td>
<td>-3.3</td>
<td>-4.7</td>
</tr>
<tr>
<td>tt50 - Simulation</td>
<td>1.7</td>
<td>-34.9</td>
</tr>
<tr>
<td>tt200 - Simulation</td>
<td>9.7</td>
<td>94.8</td>
</tr>
<tr>
<td>FC50 - Simulation</td>
<td>-10.8</td>
<td>10.8</td>
</tr>
<tr>
<td>FC200 - Simulation</td>
<td>22.0</td>
<td>-21.6</td>
</tr>
</tbody>
</table>
Analyzing travel activity determinants (1/2)

Personal travel patterns are complex data structures. ROBPCA and ROSPCA facilitate their use for modeling.

**Goal**

*Find the determinants (the variables with the highest explanatory power) of multiple-day travel behavior*

<table>
<thead>
<tr>
<th>Number of trips with baggage</th>
<th>Number of trips with purchased goods</th>
<th>Number of trips with children</th>
<th>Mean trip distance of the most frequent activity</th>
<th>Number of long distance trips</th>
<th>Number of short distance trips</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean leisure-trip distance</td>
<td>Mean shopping-trip distance</td>
<td>Mean education-trip distance</td>
<td>Mean work-trip distance</td>
<td>Mean to-home-trip distance</td>
<td>Mean escort-trip distance</td>
</tr>
<tr>
<td>Number of leisure trips</td>
<td>Number of shopping trips</td>
<td>Number of education trips</td>
<td>Number of work trips</td>
<td>Number of to-home trips</td>
<td>Number of escort trips</td>
</tr>
<tr>
<td>Number of nighttime trips</td>
<td>Number of peak time trips</td>
<td>Number of days without journey</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**PCA**

- Distorted by outliers

**ROBPCA**

- Overcame the impact of outliers

**ROSPCA**

- Improved the interpretability
Analyzing travel activity determinants (2/2)

ROSPCA reduced the original 21-dimensional patterns to 6 principal components.

The principal components were mainly loaded by two variable categories:

- **Travel impedances**
- **Journey constraints**

1. **PC1**: Travelling with children
2. **PC2**: Working
3. **PC3**: Education traveling with considered constraint
4. **PC4**: Leisure
5. **PC5**: Shopping
6. **PC6**: Escort journeys
The model under limited data conditions

The model requires personal travel activity patterns as input. Such data can be expensive and difficult to maintain. Data transferability, here statistical matching, offers a viable solution to this problem.

**Data Set A**  
**DONOR**

<table>
<thead>
<tr>
<th>Independent variables $X$</th>
<th>Dependent variables $Y_A$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Birth</td>
<td>Total number of trips</td>
</tr>
<tr>
<td>Employment status</td>
<td>Number of car trips</td>
</tr>
<tr>
<td>Household profile</td>
<td>Number of PT trips</td>
</tr>
</tbody>
</table>

**Data Set B**  
**RECIPIENT**

<table>
<thead>
<tr>
<th>Independent variables $X$</th>
<th>Dependent variables $Y_B$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Birth</td>
<td>$Y_B = \emptyset$</td>
</tr>
<tr>
<td>Employment status</td>
<td></td>
</tr>
<tr>
<td>Household profile</td>
<td></td>
</tr>
</tbody>
</table>

In our case $Y_B = \emptyset$
The model in a supply-demand interaction

The interactions among the multimodal system entities (suppliers, costumers) are investigated taking into account the supply & demand interaction and the interactions between the service providers.

**Solution**

- **Bus operator is a leader in a Stackleberg game**
- **The leader foresees the passengers’ (followers’) market shares**
- **The foreseen market shares are inferred from the equilibrated states**
- **The competing operator’s strategy is incorporated in the leader’s objective function.**
Publications


Other research topics
Paola Astegiano
• gps tracking of e-bikers
• hierarchical network planning

Bart Wolput
• optimal signal cycle timings for public transit priority

Xin Lin
• environmental zonal constraints vs. traffic efficiency

Ivan Mendoza
• quantifying aggregate supply for dynamic ride sharing
Upcoming work
Projects 2018 - 2020

• DTA
  o multiclass hybrid DNL
  o multiscale intersection models
  o equilibration with full route set
  o equilibration of non-separable problems
• DTA in pricing problems
  o bi-level network design cases with elastic demand
• co-operative AV microsimulation
  o test site Antwerp (Belgium)
  o multisource traffic operations data? → calibration
  o control structures linked to micro-simulator
Ambition to work on so much more…

• designing AV-MaaS services for Flanders
• simulation-based optimization using DTA (with Carolina Osorio)
• integration of models and data-driven approaches
  o “model of the world”
  o HLA connected simulator architecture?
• multi-day modeling
  o data-transferability (e.g. Google time lines)
• DNL of swarms (pedestrians, cyclists, autobots,…)

… if only relevant proposals got funded 😊
Thank you!

chris.tampere@kuleuven.be
+32 16 32 1673
ANNEXES
Towards convergent algorithms for non-separable problems?
Non-separabilities

- separability
  \[ c_a(t) = c_a(f) = c_a(f_a(t)) \]
- considered from a sub-problem point of view, separability is the exception
  - on same link, flows run from other sub-problems
    - while taking a step towards UE of sub-problem \( i \), one may push sub-problem \( i' \) away from equilibrium
    - this is not problematic, as mutual influence is symmetric
  - spillback, intersections with priorities, traffic management, … create asymmetric non-separability
  - time-dependent flows are asymmetrically non-separable by nature
    \[ c_a(t) = c_a(f_a(t' \leq t), f_{a'}(t' \leq t)) \]
    path costs for departure at \( t \) depend on path flows before and after \( t \) in general
Failure of swapping algorithms on simplest dynamic model...

- **Vickrey bottleneck model (1969)**
  - $N$ identical travelers with same desired arrival time $t^*$
  - bottleneck has a capacity $s \ [\text{veh/h}]
  - Travel time $T(t) = \text{time if no congestion} + \text{waiting time at bottleneck } W(t)$
    - Where $W(t) = Q(t)/s = \text{queue length divided by throughput capacity bottleneck}$
    - Assume congestion free travel time = 0
    - Travel time $T(t) = \text{waiting time at bottleneck } W(t)$

Vickrey model: cost functions and DUE conditions

- Drivers choose departure time:
  \[ r(t) = \text{departure rate function (number of departures at time } t) \]

- Private cost = travel time cost + **schedule delay cost**: 
  \[ C(t) = \alpha (\text{queuing time}) + \beta (\text{time too early}) + \gamma (\text{time too late}) \]
  - \( \gamma > \alpha > \beta \)
  - \( C(t) = \alpha W(t) + \beta (t^* - t - W(t)) \) for \( t_{\text{first}} < t < t_{\text{justintime}} \)
  - \( C(t) = \alpha W(t) + \gamma (t + W(t) - t^*) \) for \( t_{\text{justintime}} < t < t_{\text{last}} \)

- Now solve \( r(t) \) such that UE conditions hold
  - with \( C^* = \min_t C(t) \)
  - \( C(t) = C^* \Rightarrow r(t) \geq 0 \)
  - \( C(t) > C^* \Rightarrow r(t) = 0 \)
Analytical solution

- Cumulative departures and arrivals
- Queue length
- Waiting time

\[ t_0 = \text{departure time to arrive just in time} \]

- Cumulative departures
- Cumulative arrivals
- Waiting time
- Queue length

- Dept flow

- Cumulative departures and arrivals

- t first
- t'
- \( \tilde{t} = \text{departure time to arrive just in time} \)
- t''
- t* t last

- Time
Existing solutions for departure time algorithms

- less demanding models
  - bounded rationality
  - stochastic choice model (heterogeneous tastes)
- original model: quasi-reduced projection
  - but extremely slow
    - Huang & Lam (2002; 200k it))
    - see Matlab example (10k it)

Towards efficient algorithmic solutions for DUE with non-separabilities? (assuming DUE exists…)*

• reason for bad (or non-) convergence of (otherwise successful) algorithms on Vickrey bottleneck model?
  o swaps assume that only costs of space-time paths involved change, just like separable paths in space
  o but this hardly happens!
    • e.g. swap to earlier departure: will hardly increase cost at new time, at former dept. time cost may even go up!

• but there is hope: for asymmetric time non-separabilities, we know the dominant direction
  o some examples…

* existence is likely, as it was proven that path-delay operator is continuous even with spillback: Han, K., Piccoli, B., Friesz, T.L., 2016. Continuity of the path delay operator for dynamic network loading with spillback. Tr.Res.B 92, 211–233.
Typical convergence of DTA equilibrium


NB: see also ‘thin flow’ problem of Koch & Skutella (2011)
Congested route with uncongested bypass (no spillback)
Simultaneous QR gradient projection
Towards efficient algorithmic solutions for DUE with non-separabilities? (assuming DUE exists…)

- in time, we know the dominant direction of asymmetric non-separabilities
  - first converge dominant ones, later the ones having milder inverse influence = net gain
General structure of UE algorithms based on FP formulation

- split multiple OD-problems into sub-problems
  - OD-bush, O-bush, D-bush, PAS
  - time-dependent: departure time intervals
- repeat until all sub-problems converged
  - update links considered in sub-problem
    - remove unused, include new SP’s
  - equilibration step in sub-problem
    - find direction of flow swaps between links/paths
    - find step size to swap flows between links/paths
    - (update costs in network; revisit sub-problem until convergence)\(^1\)
  - (update costs in network; visit next sub-problem for one update step)\(^2\)
  - (if steps decided for all sub-problems, update costs in network; revisit all sub-problems for another update step)\(^3\)

\(^1,2,3\): update of costs should occur at either of these places in the iterations \(\rightarrow\) very determinant for convergence and computation time!

NB:
(1) is usual choice in static UE
(3) in dynamic UE (DTA)

let’s try (2)
If separability has structure, so why then try to converge over all OD(t) simultaneously?

- **Simultaneous QR gradient projection**

  Initialize: generate destination-based split proportions and DNL solution
  
  **While** (convergence criterion is not met)
  
  **For** (each time slice)
  
  **For** (each destination layer)
  
  **For** (each node)
  
  Update split proportions (destination based QR-projection)
  
  Update the DNL (marginal computation / warm start)
  
  Compute SP (marginal computation / warm start)

- **Sequential QR gradient projection**

  Initialize: generate destination-based split proportions and DNL solution
  
  **While** (convergence criterion is not met)
  
  **For** (each time slice)
  
  **For** (each destination layer)
  
  **For** (each node)
  
  Update split proportions (destination based QR-projection)
  
  Update the DNL (marginal computation / warm start)
  
  Compute SP (marginal computation / warm start)
Sequentially equilibrating sub-problems requires an efficient ‘marginal’ DNL and SP

- i-LTM
  - KWT reformulated as passing on constraints to cumulative vehicle numbers $N(t, x)$ over space-time
  - node models passing on constraints between links
  - formulated as FP, iteratively solved from warm start
  - parsimonious computations: change of $N(t, x)$ propagated in space-time only when exceeding numerical precision $\epsilon$
  - similar FP formulation with warm start of dynamic SP problem

Grid with interpolation & implicit algorithm (no CFL)

Iterate each (larger) time step until convergence

warm start: initial guess from previous (nearby) simulation

MaC: at each iteration, only recompute grid points whose precedents changed significantly in previous iteration (NB: in smart order, because Gauss-Seidel)

Sequential QR gradient projection
Convergence
Towards efficient algorithmic solutions for DUE with non-separabilities? (assuming DUE exists…) 

• in time, we know the dominant direction of asymmetric non-separabilities  
  o first converge dominant one, later the one having milder inverse influence = net gain 

• in general, how to discover non-separabilities and how strong their mutual influence is?  
  o analytical approximations of path-delay operator (Lu et al., 2013; Nezamuddin & Boyles, 2014)  
  o numerical approximations of path-delay operator (Himpe et al., 2016)  
  • parsimoniously identifying which other sub-problem changes along with currently considered sub-problem
Numerical sensitivity for detecting and sorting non-separability?

- sequential DUE-iterations
  - impact of changes by equilibrating sub-problem can be identified and quantified, hence sorted
  - smart order among non-separable sub-problems
    - first dominant sub-problems causing largest disequilibration of connected problems AND farthest from equilibrium
    - later those depending on dominant ones, but not causing much disequilibration in inverse direction