Modelling Daily Demand Flows in the Era of Big Data

Francesco Viti

MobiLab Transport Research Group

Faculty of Sciences, Technology and Communication, University of Luxembourg

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MobiLab

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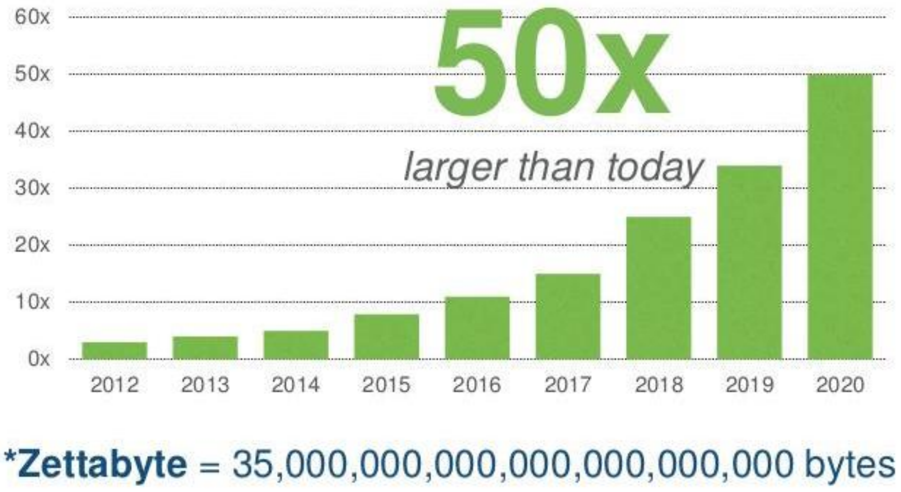
Big Data: some general stats

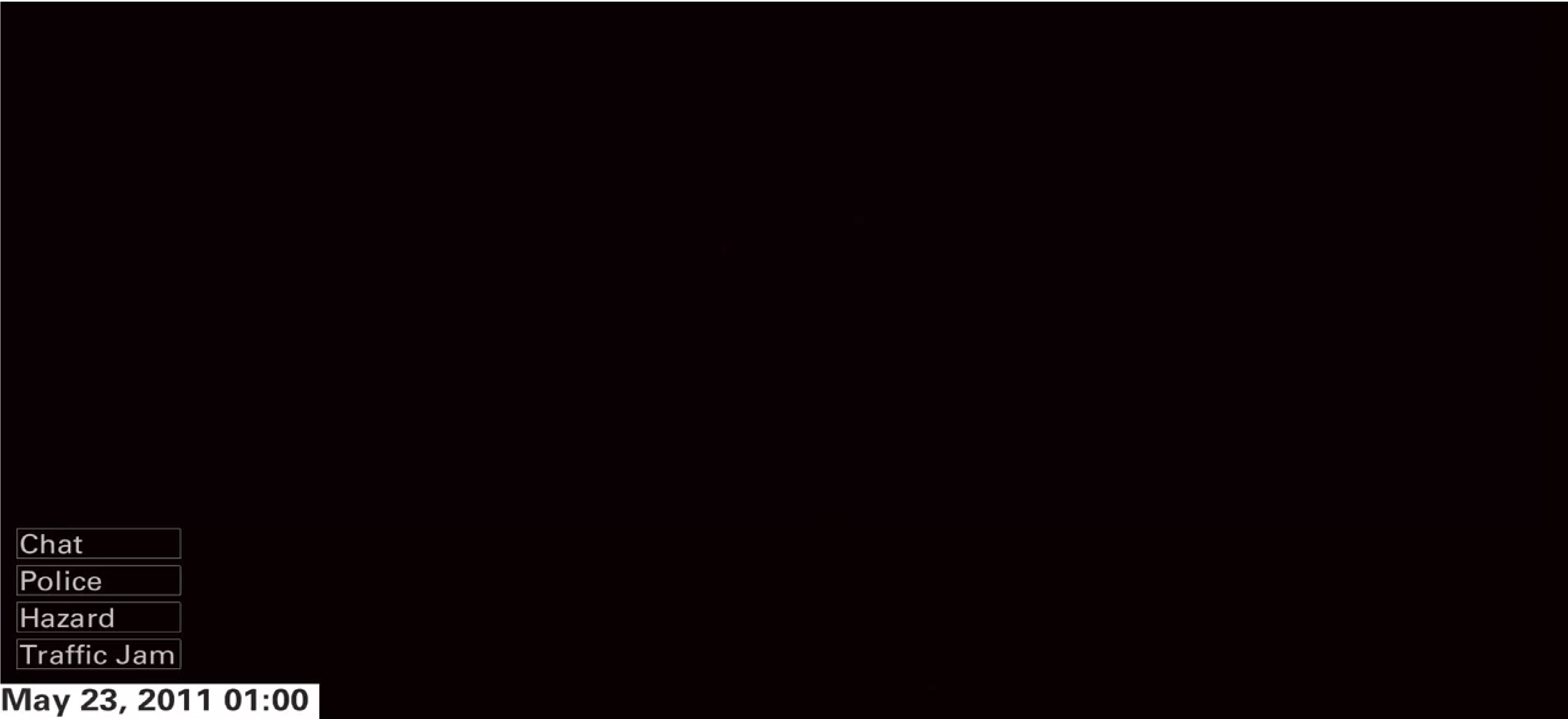
- 3 Zetabytes of data in the digital universe in 1 year
- By 2020 1.7 megabites of data created every second for every person on earth
- Over 5 billion people are calling, texting, tweeting and browsing on mobile phones worldwide
- Data production will be 50 times greater in 2020 than it was in 2010



Sources: McKinsey, EMC Corp.

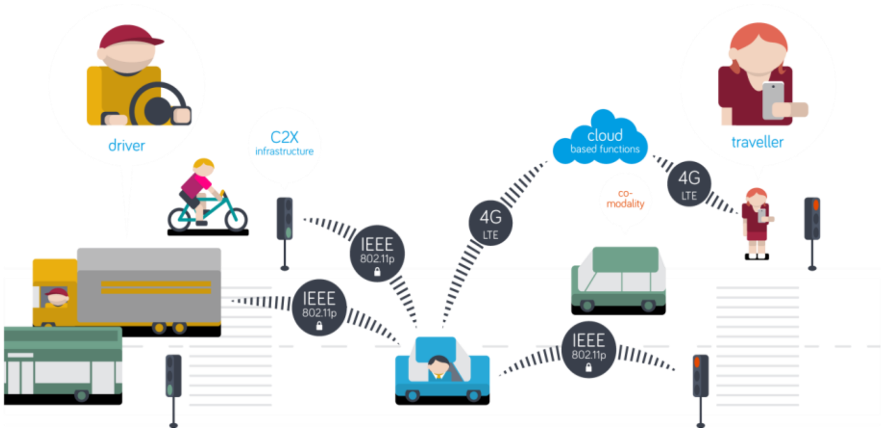
The era of Big (mobility) Data

Big Data fireworks from Waze users



Towards a Smart Mobility vision: connecting everyone & everything

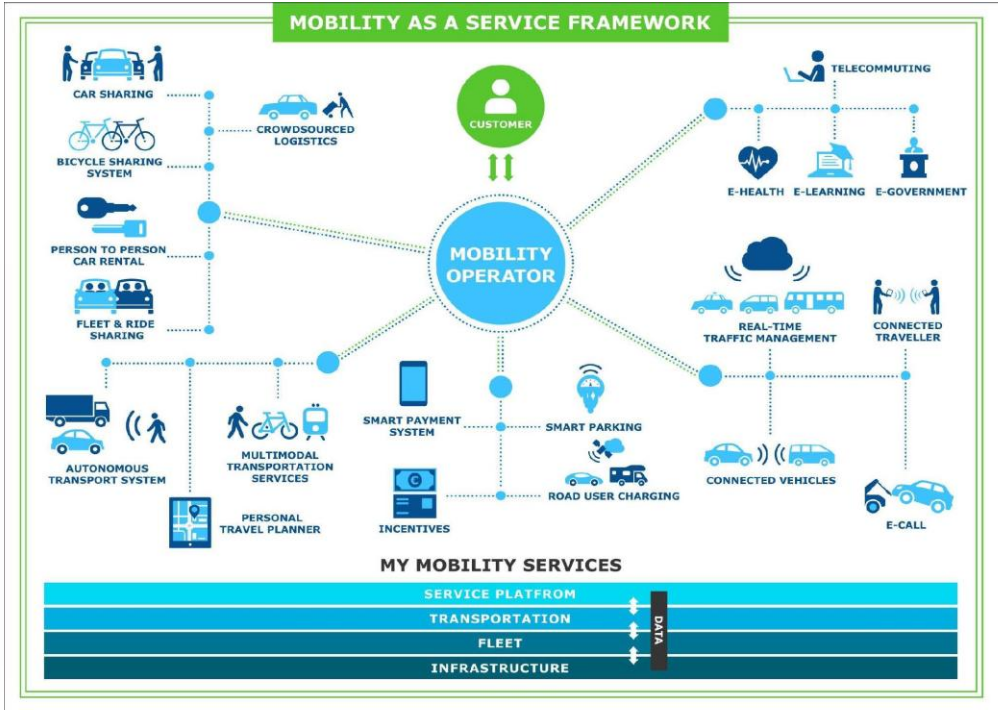
- Exploiting data sharing and connectivity of travellers, vehicles and infrastructure through ICT/IoT enables unprecedented performances
  - Better seamless information
    - Through **Big and Open Data**
    - Through advanced **DSS for the travellers**
  - Better integrated management: C-ITS
    - Through **Cooperative ITS technology**
    - Through advanced **DSS for the managers**
  - Better availability and use of services
    - Through incentivizing **collaborative mobility**
    - By exploiting **multimodal mobility** solutions



https://www.collaborative-team.eu

A (likely) Smart Mobility future

- Mobility-as-a-Service: Shifting from vehicle ownership to vehicle *usership*
  - Sharing Economy
  - Integrated multimodal options
  - Mobility budget schemes
  - Connected & autonomous vehicles



Challenges for the transportation research community

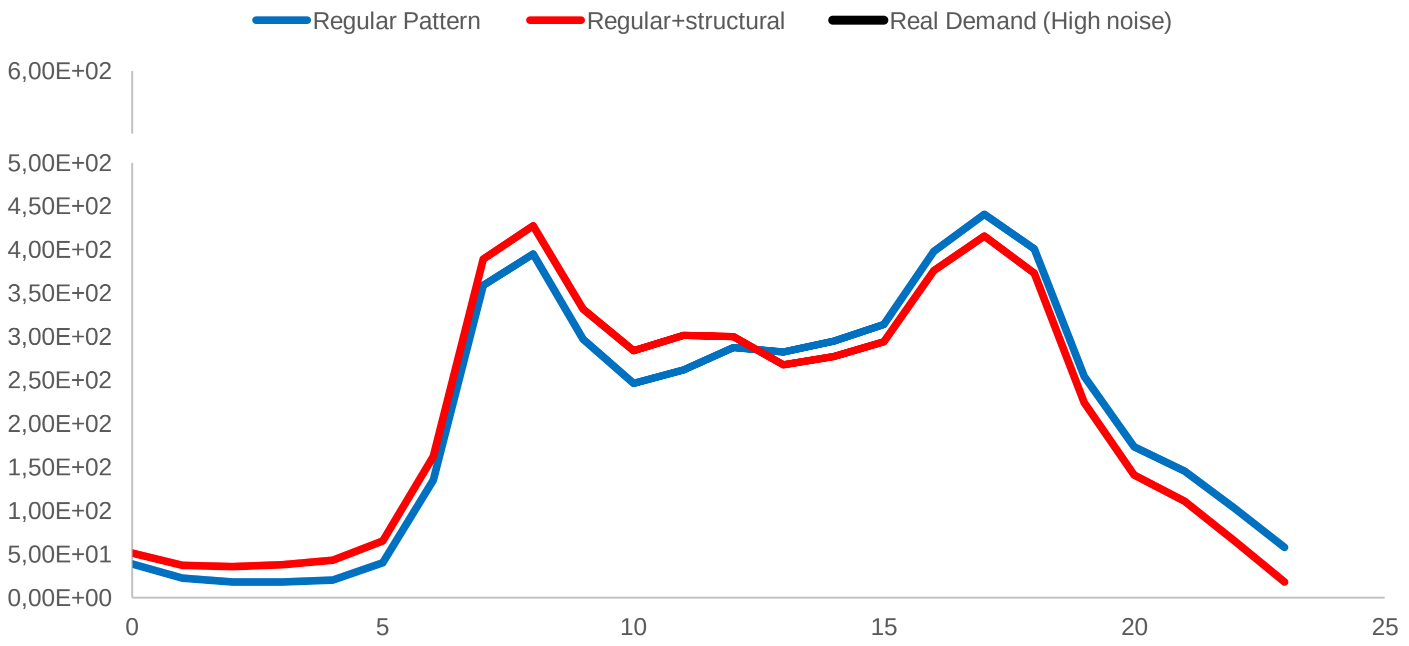
- How to organise Smart Mobility systems in an efficient way?
  - Integration of services, need for new network design approaches
  - Mobility budget schemes, need to quantify willingness to pay and to change
  - New emerging technologies and solutions conceived with unprecedented frequency
- How to predict demand and supply systems in future Smart Mobility systems?
  - Missing historical data, early MaaS systems currently tested
  - Complex interoperability of services, value added effects, transition towards CAVs
  - Changing mobility habits, attitudes, values of times,…
- Are our transport models ready?
  - Will our supply models be the same?
  - Will our demand models be accurate enough?

Modelling Daily Demand Flows

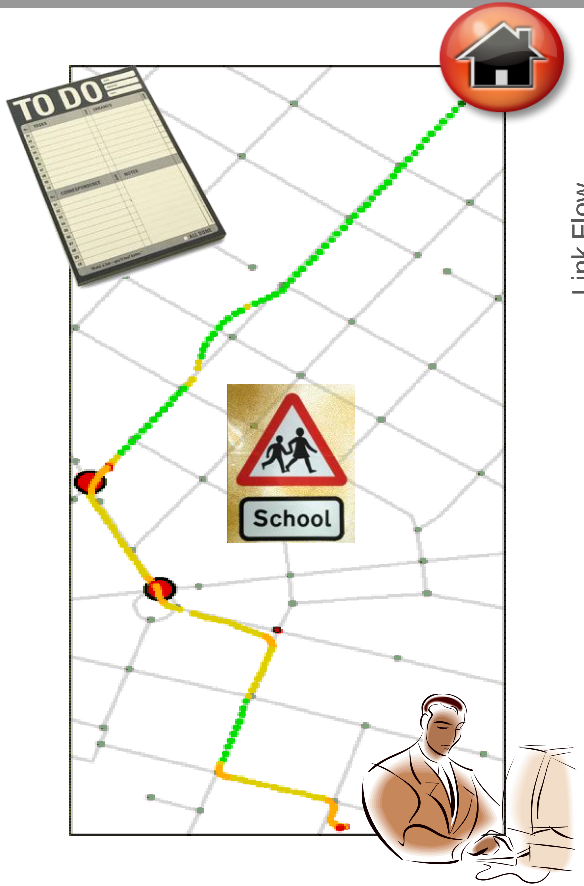
And some ingredients for reliable estimation

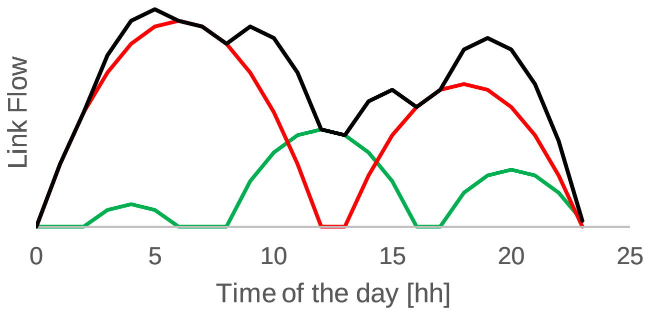
Distinguishing regular daily demand patterns

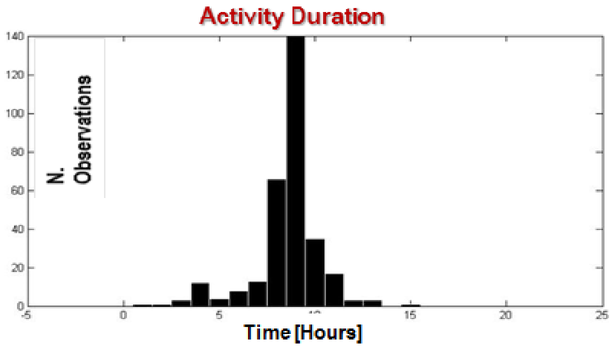
True Demand = regular pattern + structural deviations + random fluctuations

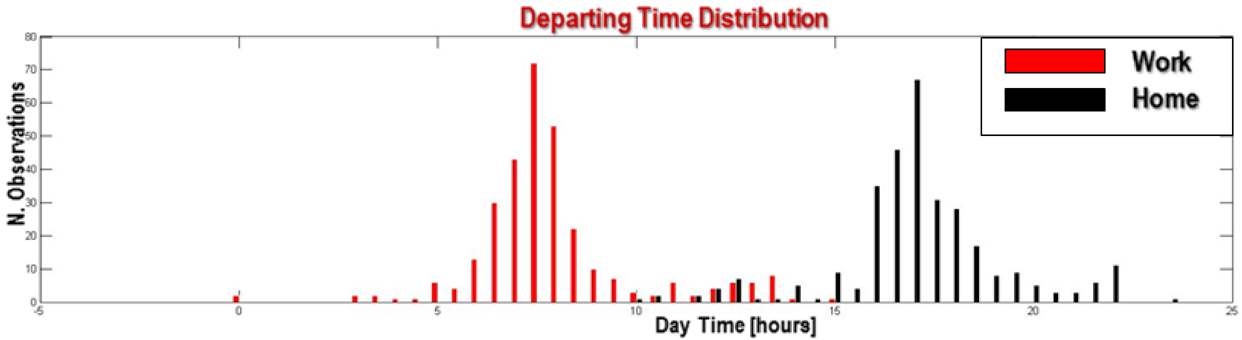


The complexity of daily mobility patterns

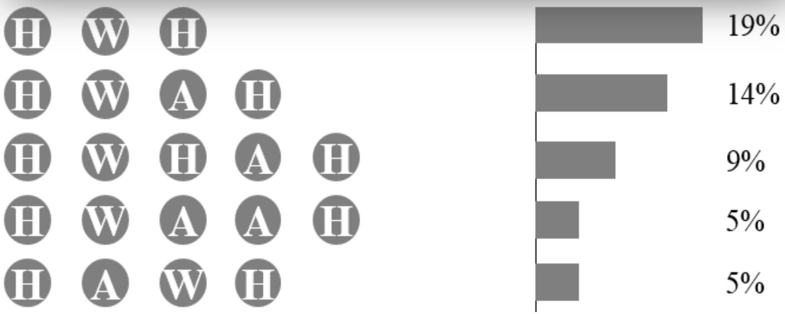


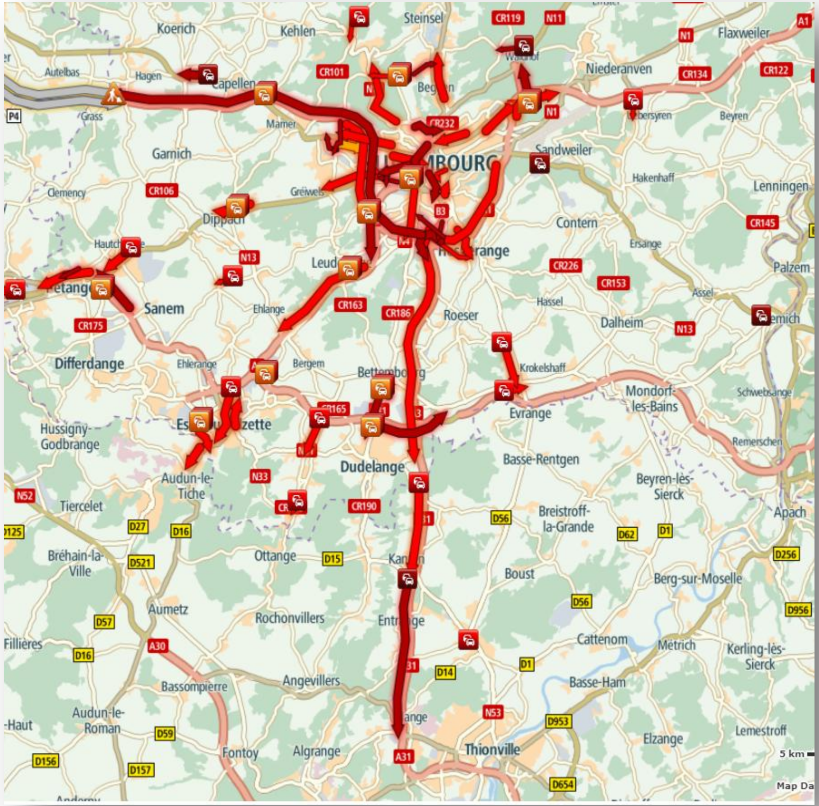






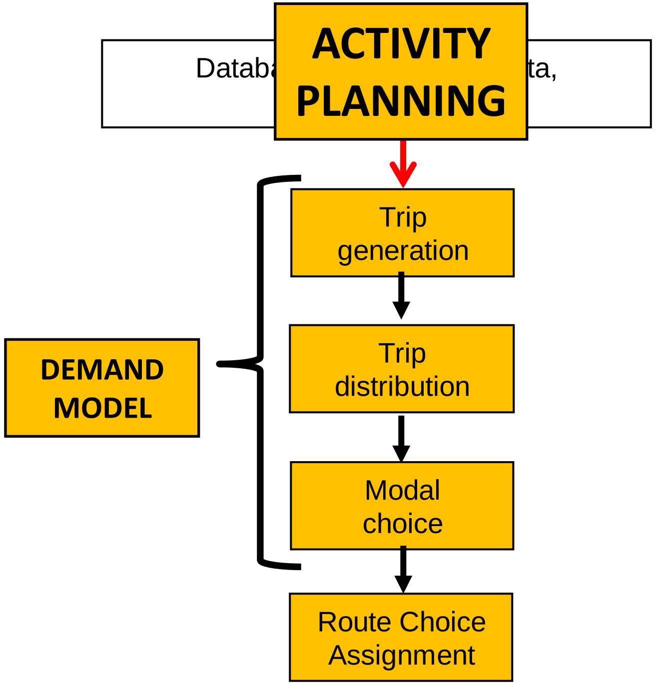
The complexity of daily mobility patterns in Luxembourg



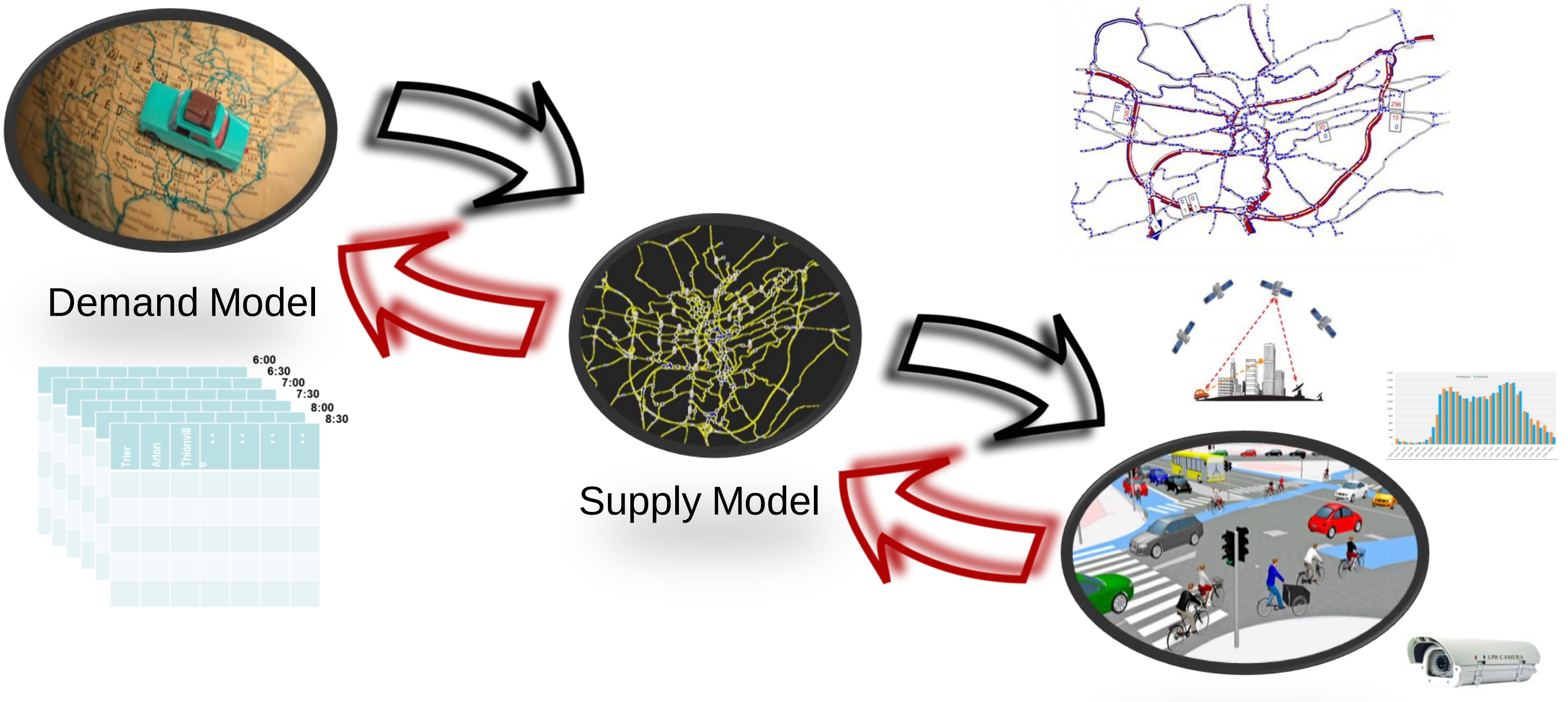


The traditional transport modelling approach

- The ‘traditional’ 4-stage model
  - Socio-demographic data
  - Travel surveys
  - Trip-based, busiest peak hour
  - Generally not suited for dynamic demand modeling
- Activity-based models
  - Schedule-based
  - Able to capture complex daily activity chains
  - Hard to calibrate and to get suitable data
  - Difficult to get consistent aggregated demand flows
  - Currently not much used for estimating daily flows



The current state of the practice for calibrating transportation models



Traffic models, data collection and estimation methods

Infrastructure Planning

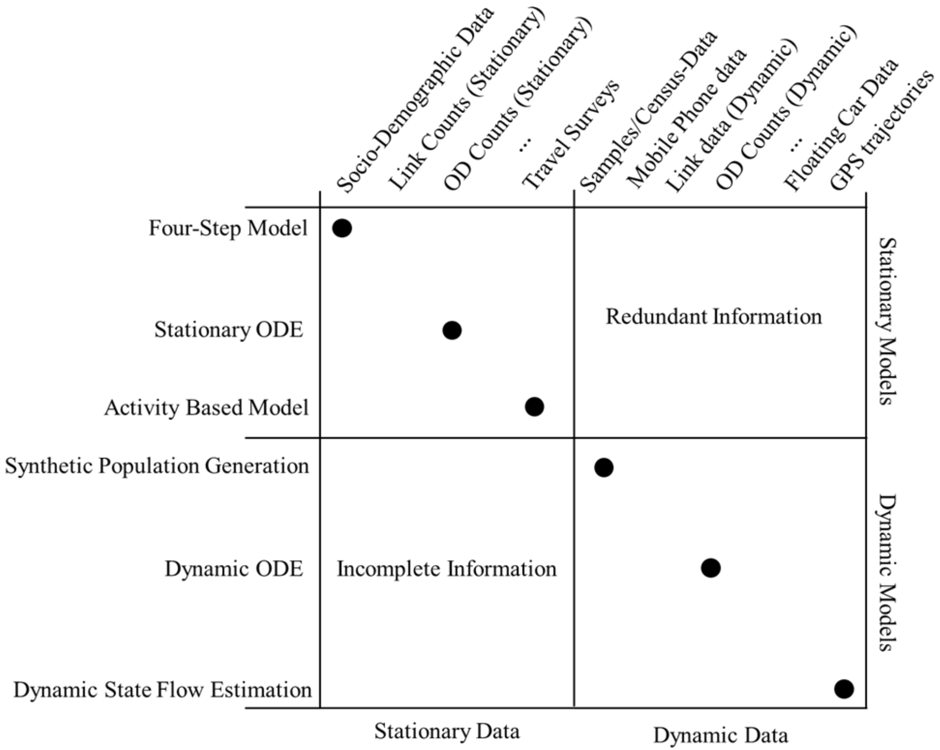
- Travel demand forecasting (static, quasi-static)
  - 4-step models, activity-based models
  - OD matrix correction / adjustments from traffic data

Dynamic Traffic Management

- Dynamic demand estimation (dynamic, offline)
  - Quasi-dynamic / sequential / simultaneous
  - Simulation DTA-based

Real-time information & management

- Dynamic state flow estimation (dynamic, online)
  - Data-driven
  - Model-driven



Acknowledgment: Guido Cantelmo (UL)

General bi-level dynamic demand estimation problem framework

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Goal: find most likely demand and supply characteristics that reproduce the data

$$\mathbf{x} = \arg\min_{x} \left[\underbrace{\sum_t \sum_j f_1(x_j, \hat{x}_j)}_{\text{Distance btw estimated and prior matrix}} + \underbrace{\sum_t \sum_i f_2(y_i, \hat{y}_i)}_{\text{Distance btw simulated and observed traffic states}} \right]$$

x = demand flows
y = traffic flows

$$\text{s.t.} \quad y_i = \sum_{j \in J_i} A x_j = \sum_{j \in J_i} B(x) P(x) x_j$$

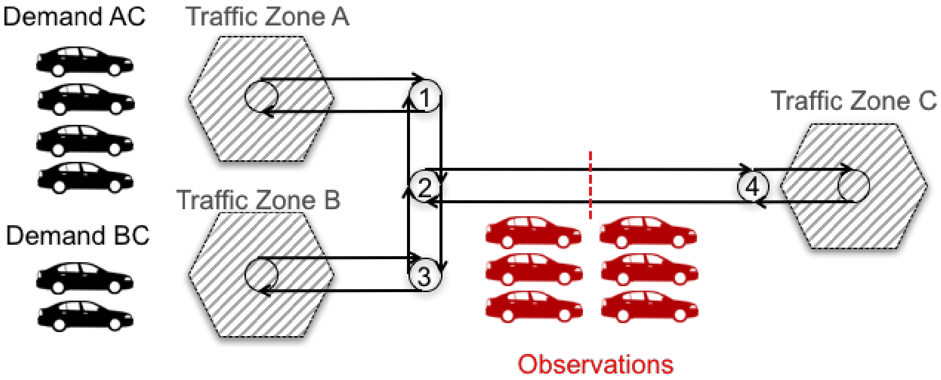
Traffic propagation functions (DNL) → $B(x)$

Travel behavior functions (DTA) → $P(x)$

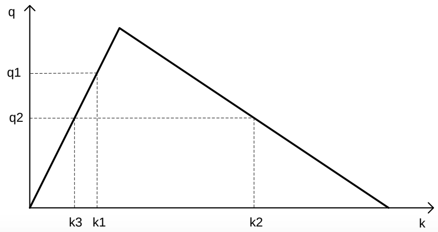
- Some (well-known) issues
  - Complex dynamics caused by travel behavior
  - Traffic models (DNL/DTA) course representation of real traffic propagation
  - Highly combinatorial & non-linear problem

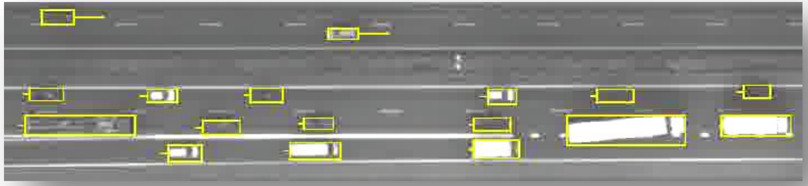
The under-determinedness problem

Spatial under-determinedness

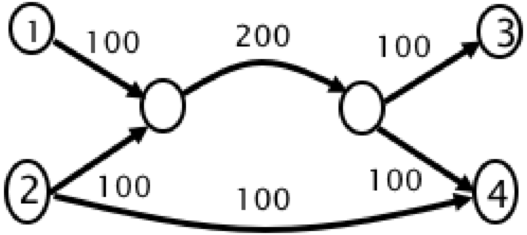


Non-linear mapping link-OD flows





Non-unique link-path-OD relations



O\D	3	4
1	0	100
2	100	100

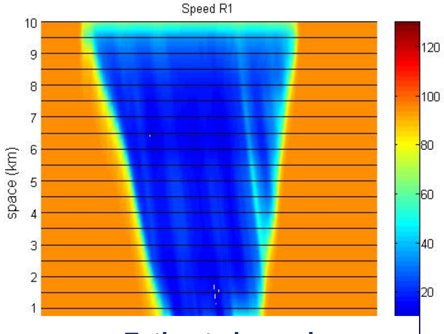
O\D	3	4
1	50	50
2	50	150

A simple example: Antwerp network

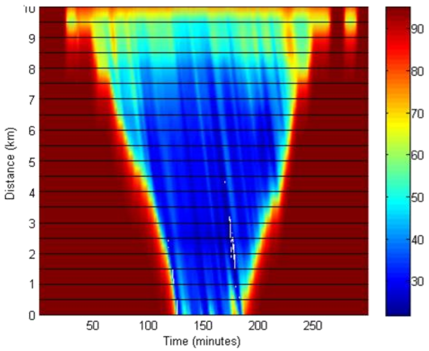
- Few route choice options
- Only traffic counts used for calibration
- Wrong structure of the demand matrix

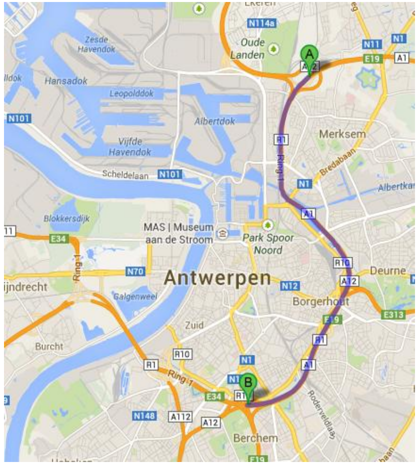
- Spoiler: Better data and better models will solve the issue

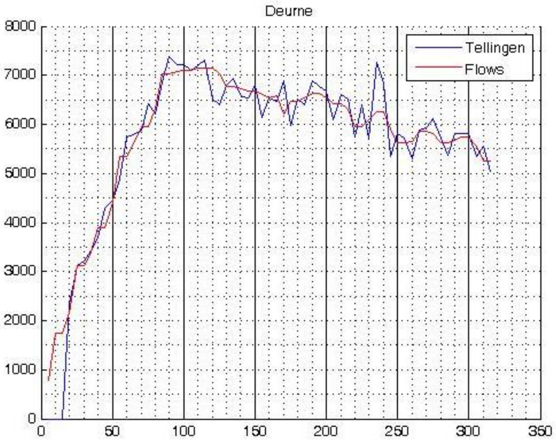
Measured speeds



Estimated speeds







Acknowledgments: Rodric Frederix Chris Tampere (KU Leuven)

Some ingredients for reliable dynamic traffic estimation

1. **Demand information**
    1. Demand data
    2. Demand models
2. **Data quality**
    1. Sensor locations
    2. Different data types
3. **Dynamic traffic flow models**
    1. Simulation of traffic flow propagation
    2. Reproduction of congestion dynamics
4. **Travel behavior models**
    1. Travel choice models
    2. Traffic assignment and equilibrium
5. **Optimisation algorithms**
    1. Structure of the estimator
    2. Gradient vs. gradient-free methods

Reduce solution search space and information reliability

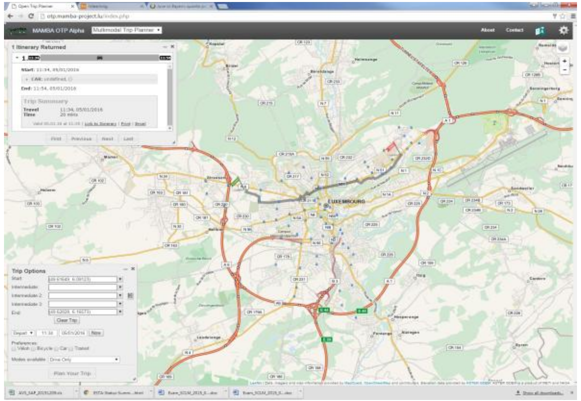
Reduce the mismatch between model and reality

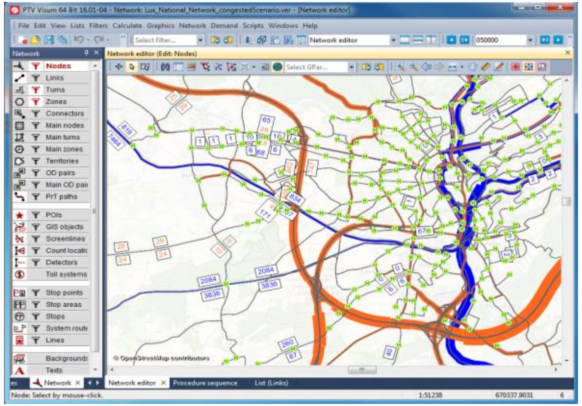
Helps for orientating in the solution space in the right direction

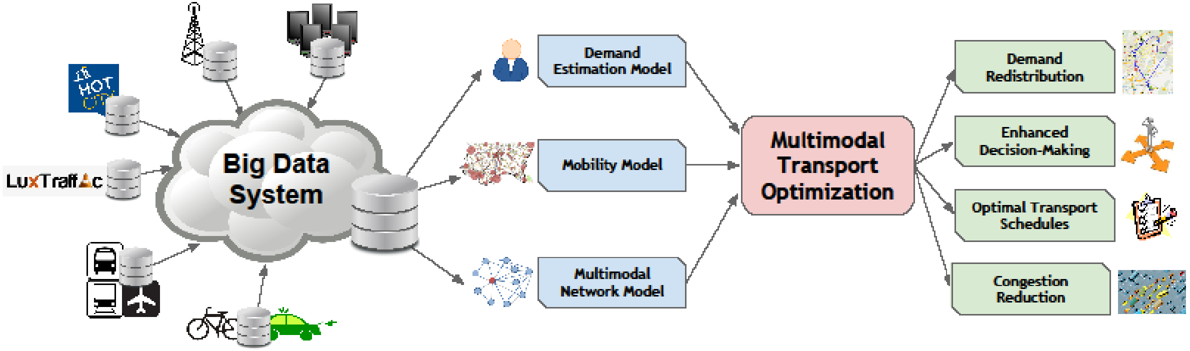
Current research directions at UL using Big Data

http://otp.mamba-project.lu/

- Big Data-based applications
  - Mobility analysis
  - Demand estimation
  - Multimodal modelling
  - Personal Travel planners
- Real data available of Luxembourg
  - Mobile phone data (Post)
  - Smartphones (& smartwatches) (go2uni platform)
  - Other ‘more traditional’ (OpenData Portail)







Using mobile phone data for daily demand production and spatial-temporal distribution

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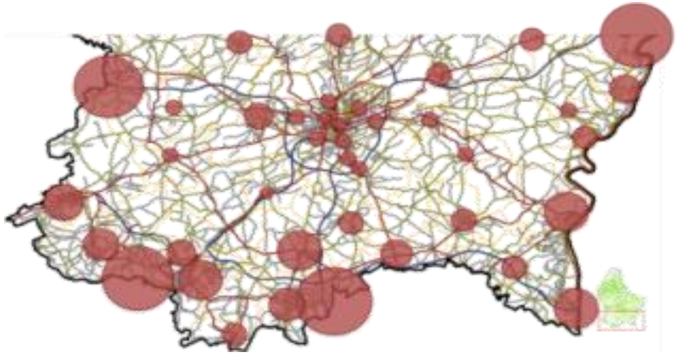
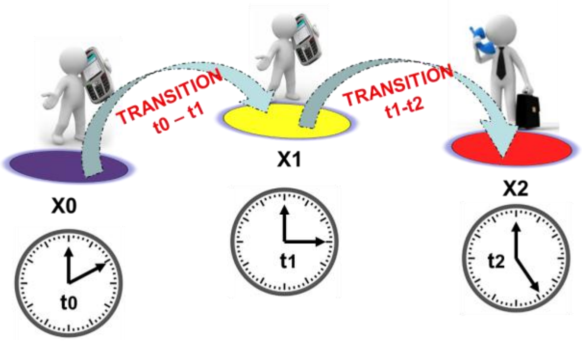
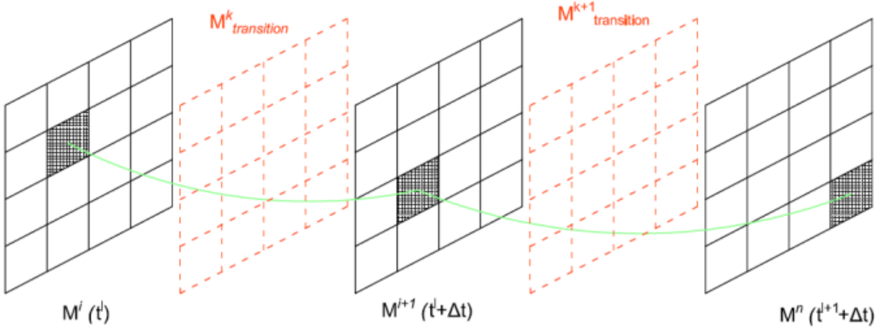
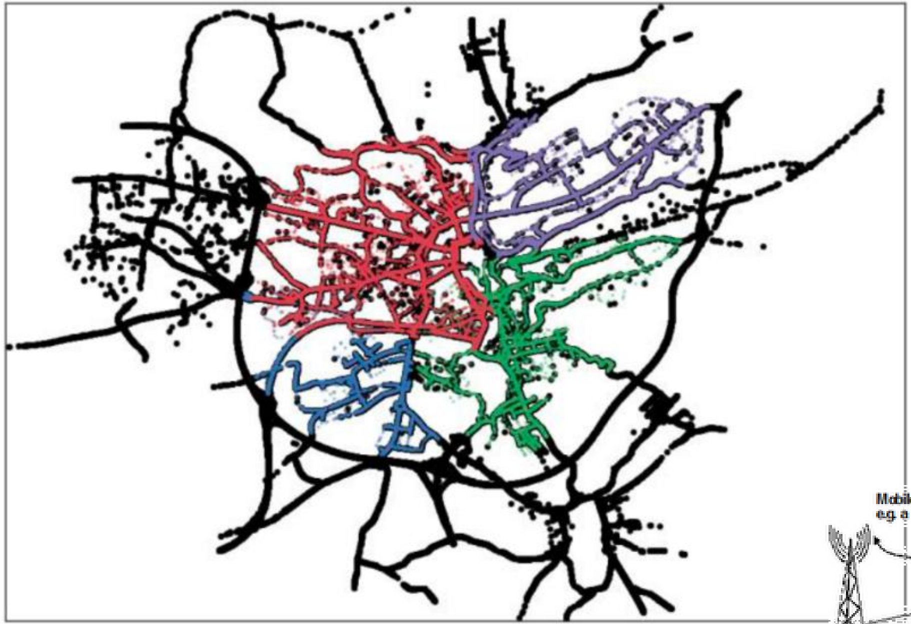


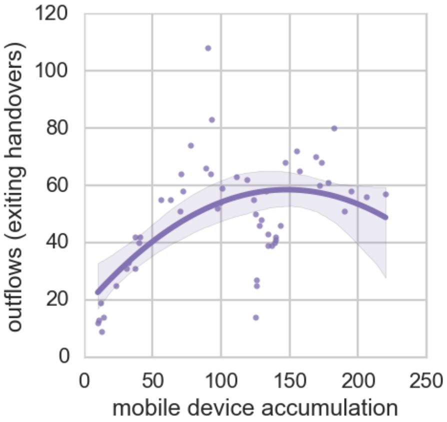


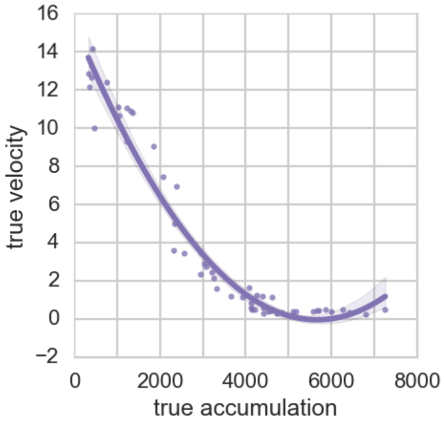


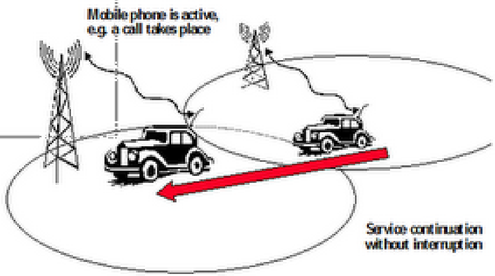
Acknowledgments: Simone Di Donna & Guido Cantelmo (UL)

Using mobile phone data for network state estimation: Macroscopic Fundamental Diagram



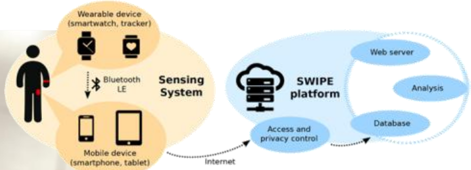


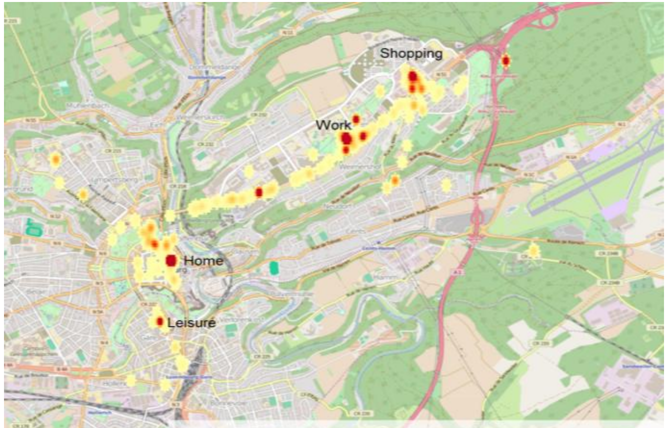




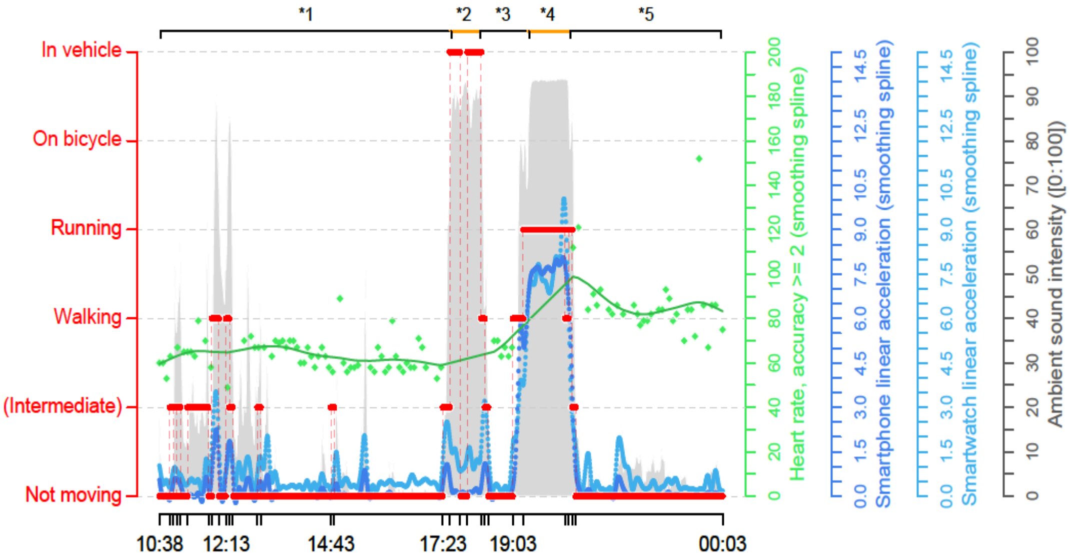
Acknowledgments: Raphael Frank & Thierry Derrmann (SnT)

Using smartphone (and smartwatch) data for modelling individual daily mobility patterns



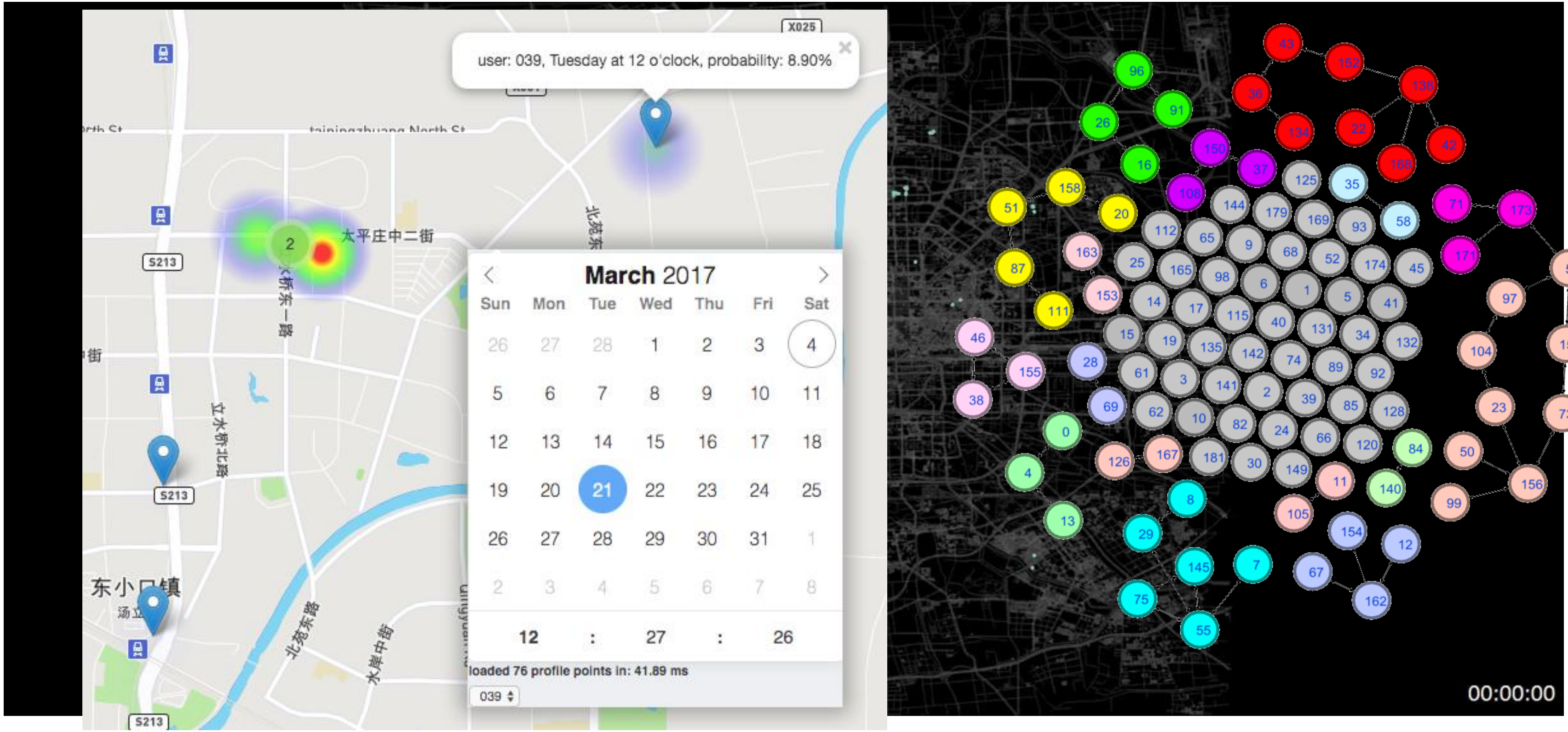


Location identification and classification



Acknowledgments: Bogdan Toader, Sebastien Faye (UL)

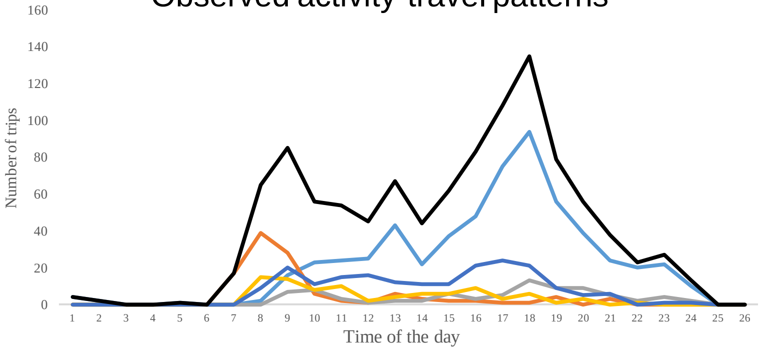
Using smartphone data for predicting and correlating daily demand patterns



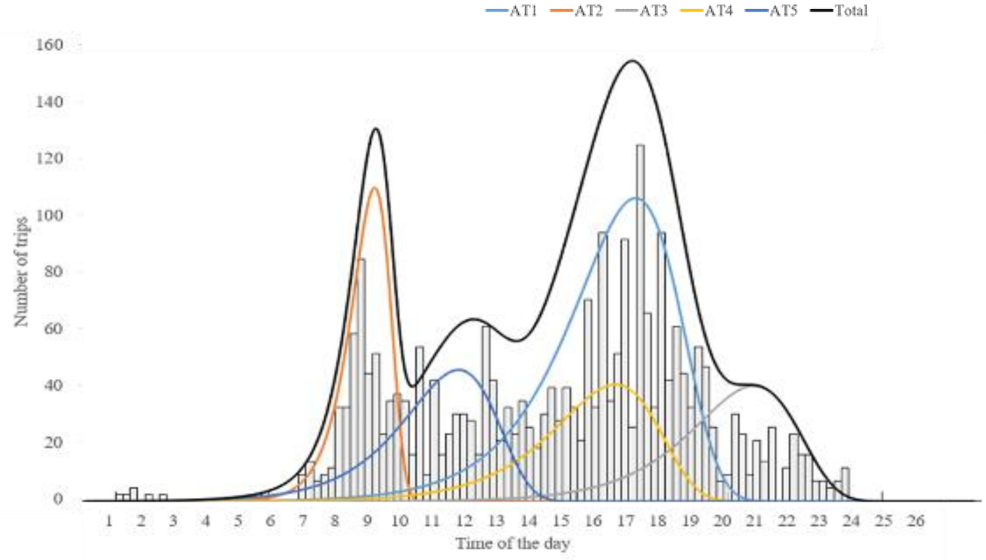
Acknowledgments: Bogdan Toader (UL)

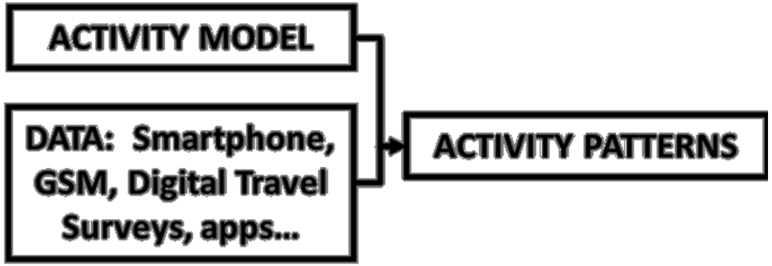
Generating purpose-specific demand information from individual mobility data

Observed activity-travel patterns



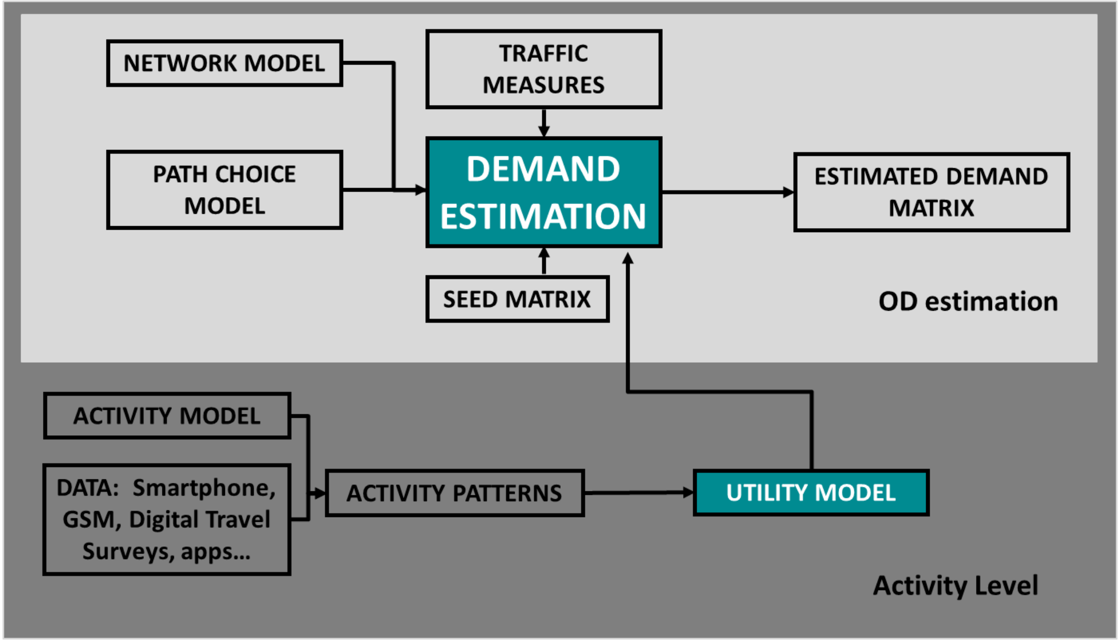
Generated demand

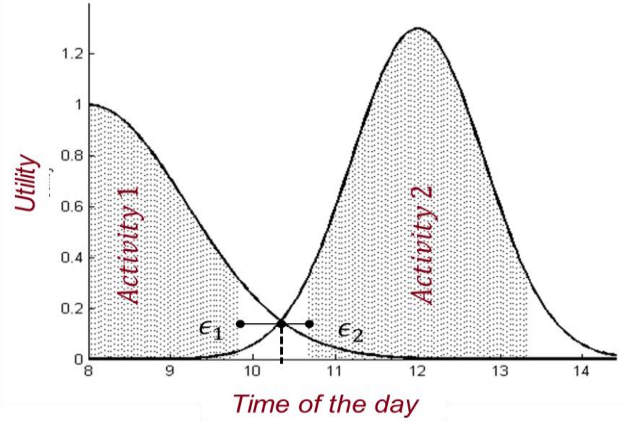


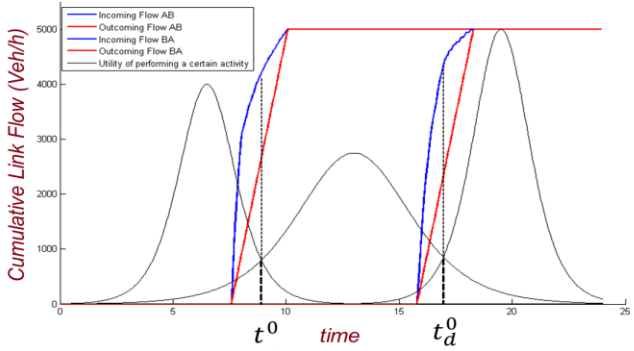


Acknowledgments: Ariane Scheffer (UL)

Including activity scheduling in daily demand estimation (1)

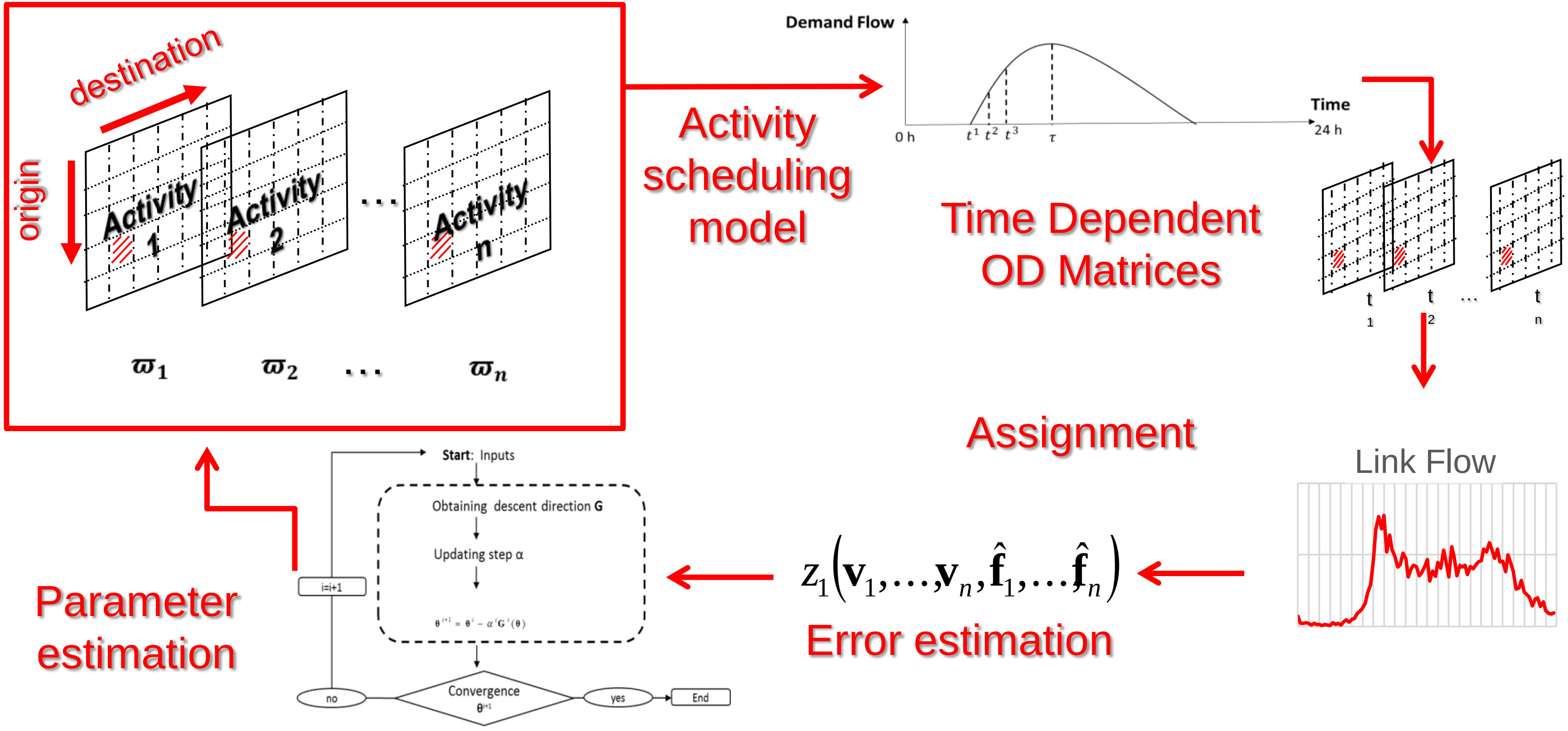






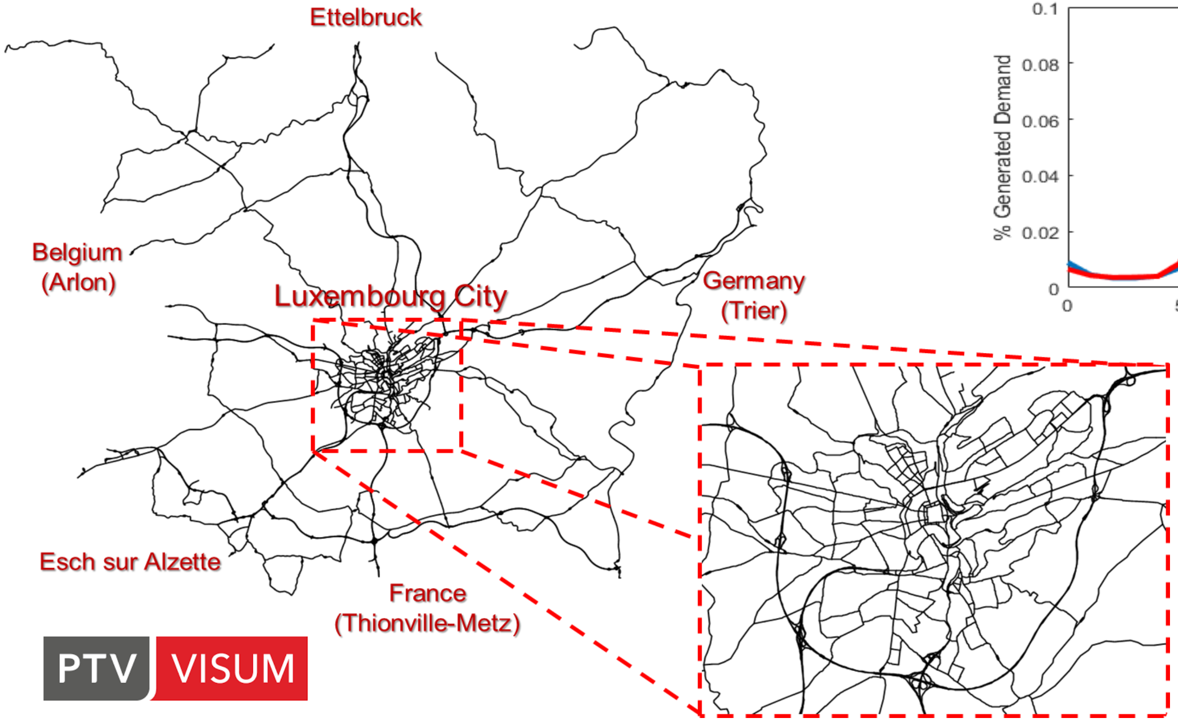
Acknowledgments: Guido Cantelmo (UL)

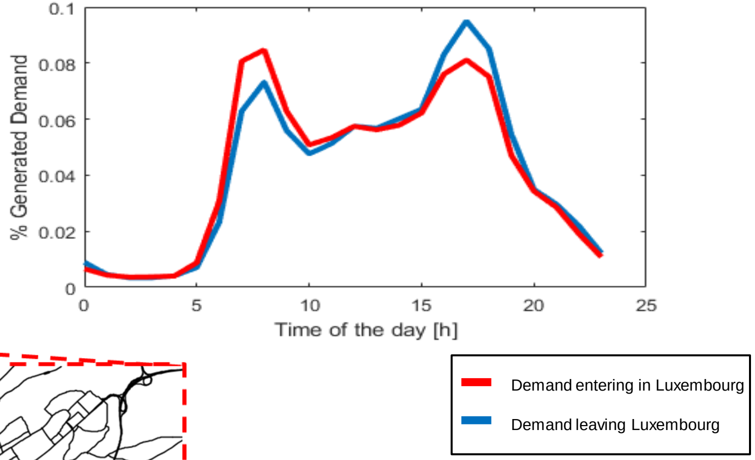
Including activity scheduling in daily demand estimation (2)



Acknowledgments: Guido Cantelmo (UL)

Application on a real sized network: Luxembourg

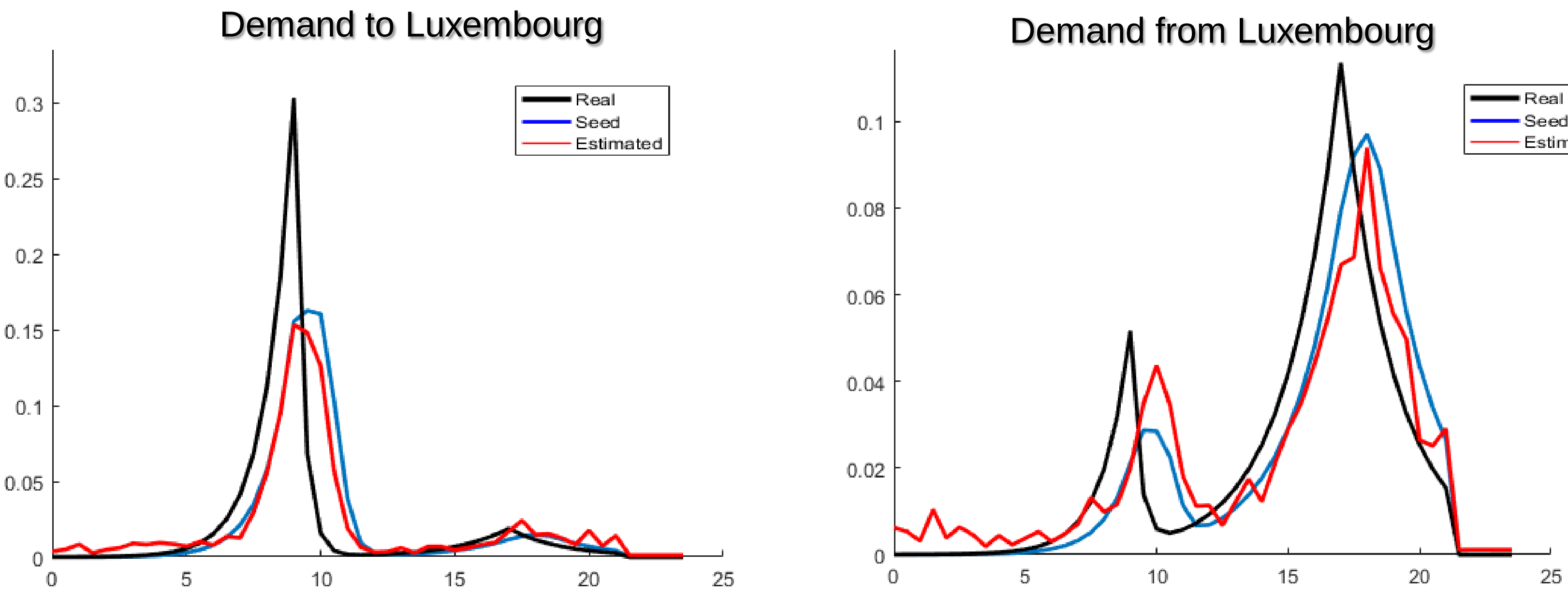




PTV VISUM
the mind of movement

Data provided by POST Luxembourg

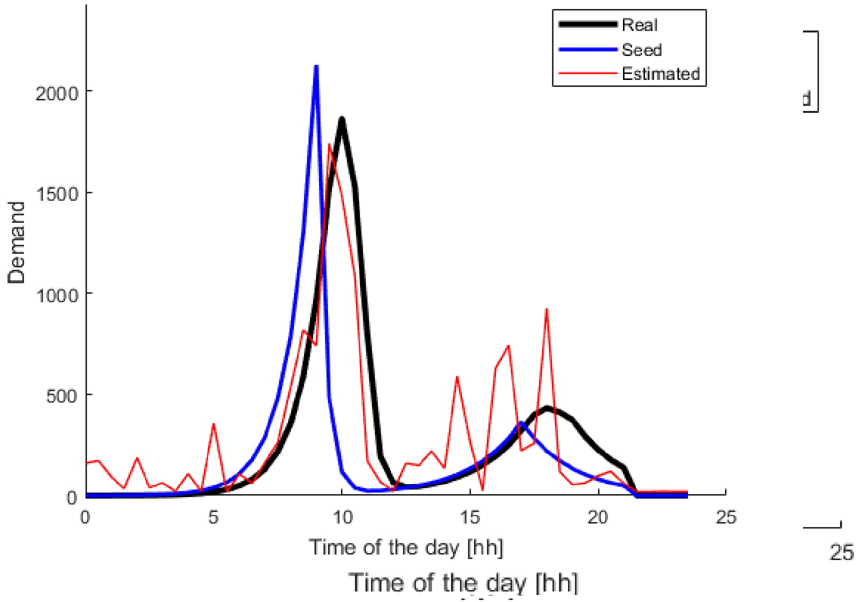
Benchmarking scenario: Demand in/out of Lux City



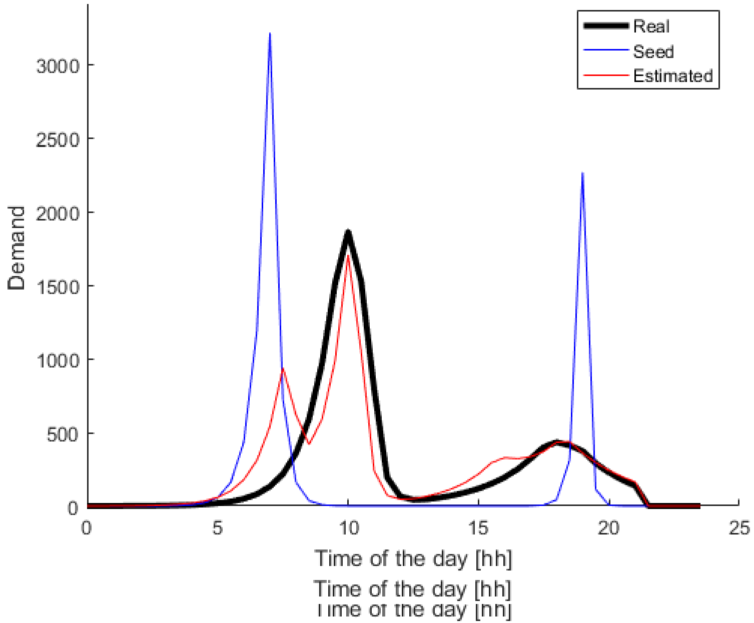
Acknowledgments: Guido Cantelmo (UL)

Results of daily demand flows on some OD pair

Trip-Based scenario: Classical approach

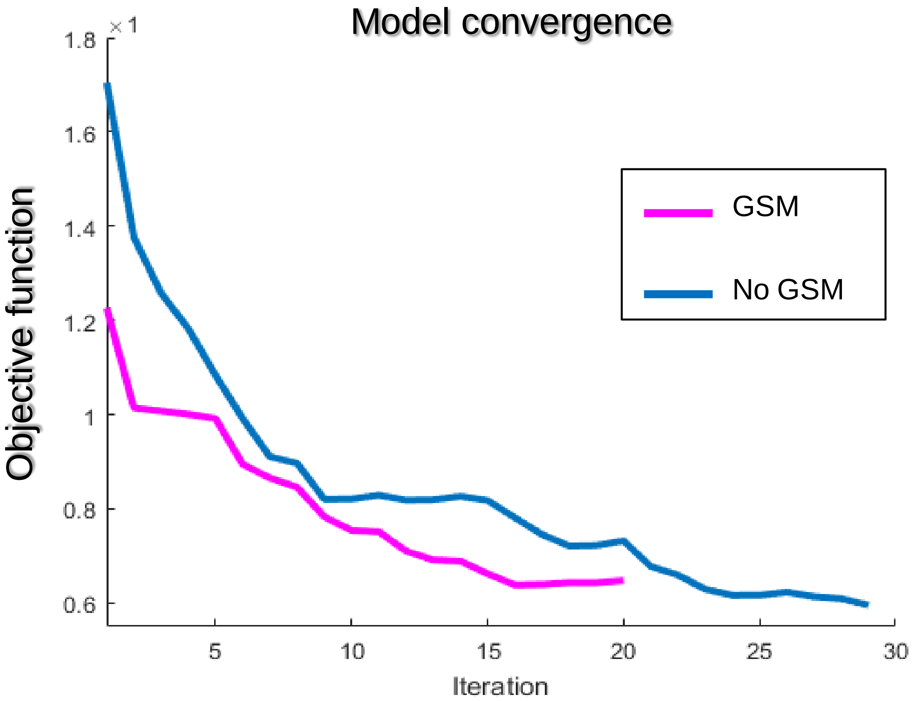


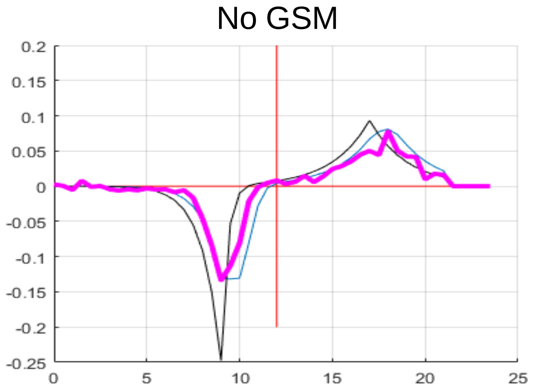
Utility-based formulation

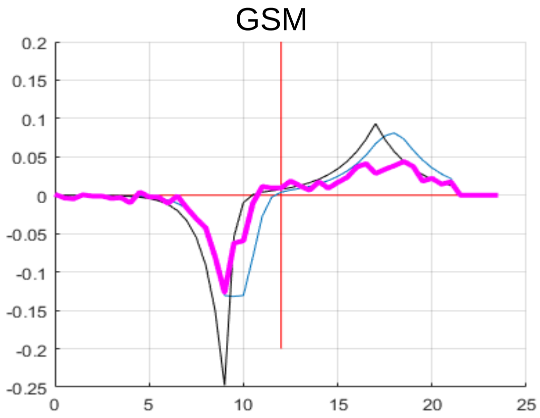


Acknowledgments: Guido Cantelmo (UL)

including mobile phone data for demand flow production







Acknowledgments: Guido Cantelmo (UL)

Future perspectives

- The future is uncertain, but…
- The future is bright: **A lot still has to be done**!!!
- A unified model-data-driven modelling approach needed
  - Travel demand models with dynamic flow estimation models
  - Behavioural and data science approaches
  - Interdisciplinary effort
    - Engineering
    - Computer Science
    - Social sciences
    - Transport Economy
    - …

Outlook and closing remarks

- New Big Data gives opportunities for improving our demand models
  - Understanding mobility needs
  - Forecast future activity-travel patterns
  - Enable users with enhanced information
- Examples of transport applications
  - Dynamic traffic modelling
  - Multimodal travel planning
  - Decision support services
  - Transport systems optimisation

- New challenges needed to model the demand and supply of the future

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www.mobilab.lu francesco.viti@uni.lu

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