EPFL

Disal

Signals, Instruments, and Systems – W12

Mobile Sensor Systems for Environmental Monitoring

Outline

- Motivation
  - Air and water quality monitoring
  - Environmental sensing

- Mobile sensor systems
  - The OpenSense project
  - Mobility impact
  - Statistical mapping techniques

Motivation

Motivation for Spatially Dense Air Quality Monitoring

Air pollution in urban areas is a global concern

- affects quality of life and health
- urban population is increasing

Air pollution is highly location- and time-dependent

- traffic chokepoints and rush hours
- urban canyons and weather
- industrial installations and activities

Air pollution monitoring today

- Sparse, stationary and expensive stations
- Spatial interpolation with mesoscale models

Motivation for Spatially Dense Water Quality Monitoring

Fresh water quality monitoring is a global concern

- Fresh water reservoirs are under pressure
- Global population is increasing
- Water ecosystems are not well understood

Water quality is location- and time-dependent

- natural transport phenomena, weather
- interaction lake physics and biology
- waste treatment plants, industrial installations, agricultural activities

Water quality monitoring today

- Stationary research stations leveraging vertical profilers
- Operational boats equipped with dedicated sensing equipment

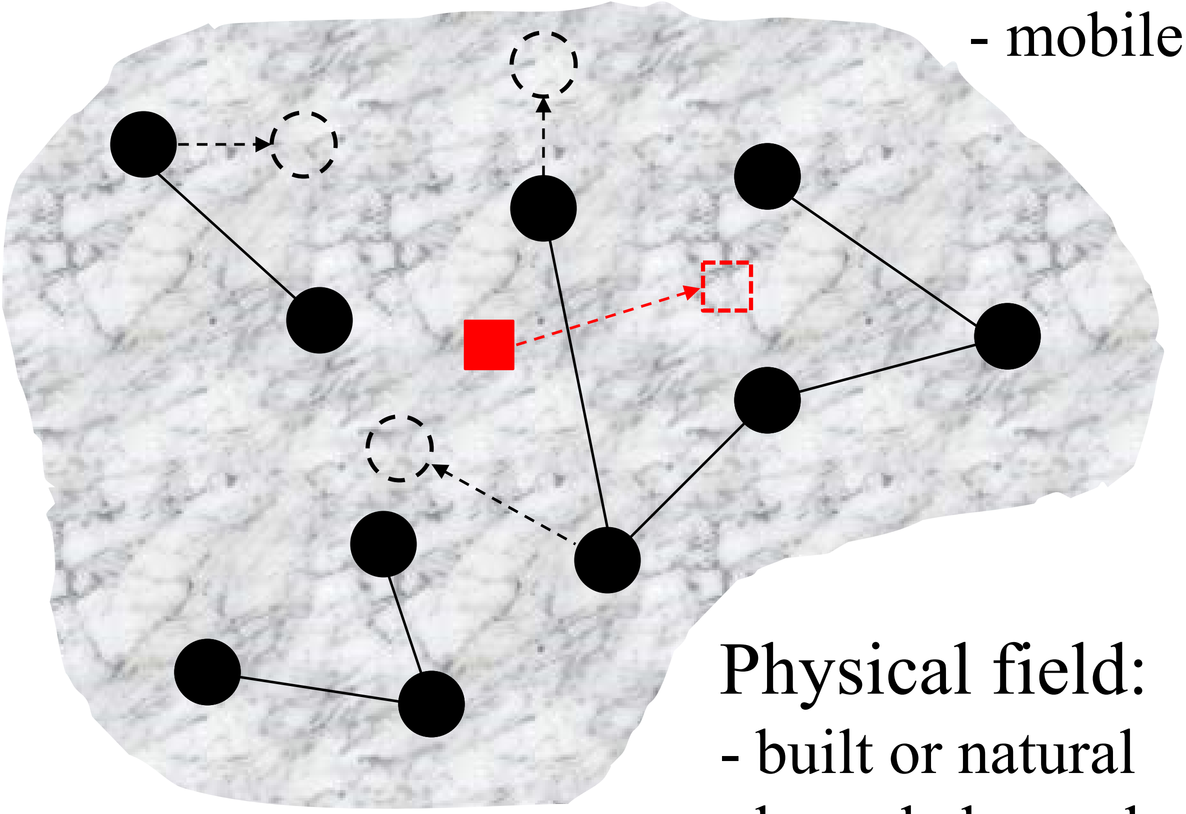
LéXPLORE monitoring station, Lake Geneva

CIPEL monitoring boat, Lake Geneva

Environmental Monitoring

Typical solution in environmental monitoring:
- sparse sensing
- expensive
- field estimation via models
- possible mobility

Distributed solution for augmentation:
- size, cost
- number
- networked
- mobile



Physical field:
- built or natural
- bounded or unbounded
- 2D or 3D

Air Quality Monitoring

Importance of Air Quality

On March 25, 2014, the WHO reported:

"… **in 2012 around 7 million people died** – one in eight of total deaths – as a result air pollution exposure. This finding more than **doubles previous estimates** and confirms that air pollution is now the **world's largest single environmental health risk**. "

"The new estimates are not only based on more knowledge about the diseases caused by air pollution, but also upon better assessment of human exposure to air pollutants **through the use of improved measurements and technology**."

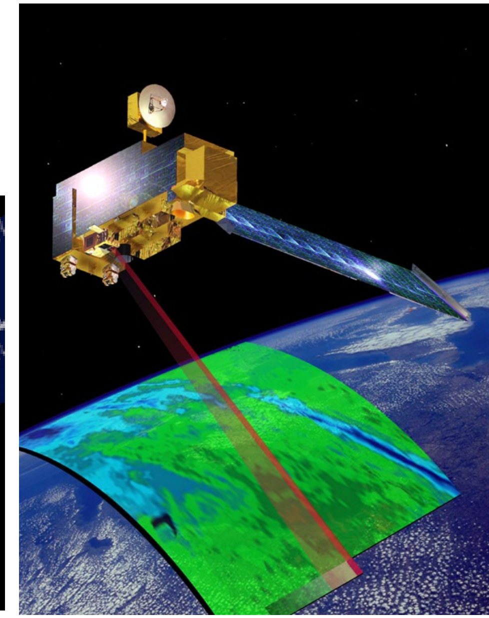
http://www.who.int/mediacentre/news/releases/2014/air-pollution/en/

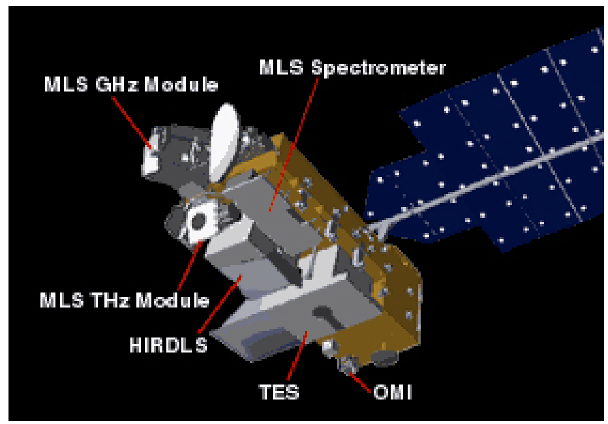
Monitoring Today

Satellite-based remote sensing

Examples:

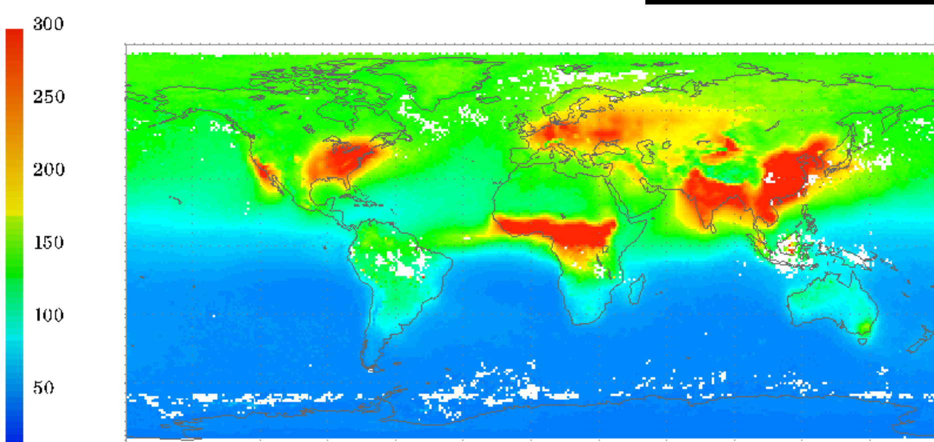
- Measurements of Pollution in the Troposphere (MOPITT on Terra satellite)
- Ozone Measurement Instrument (OMI on Aura satellite)



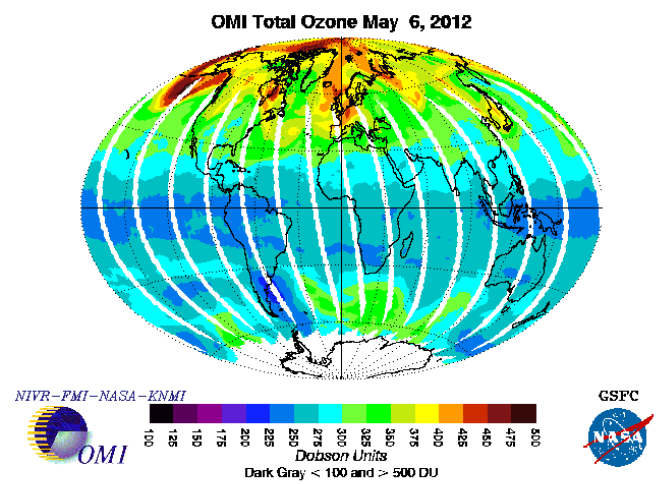


Features:

- daily scans
- large coverage
- homogeneous quality
- sensitive to cloud coverage
- low resolution

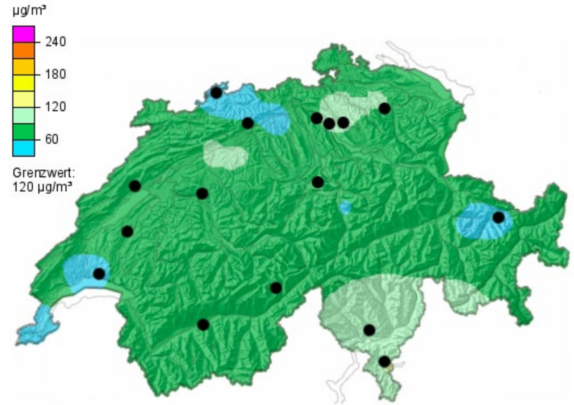


MOPITT CO Mixing Ratio at Surface (ppbv)



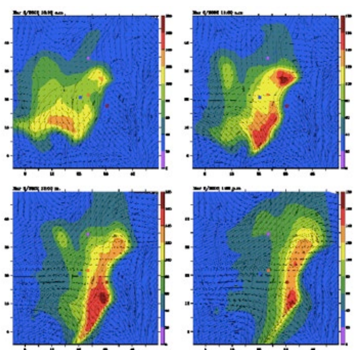
Monitoring Today

Stationary and
expensive stations



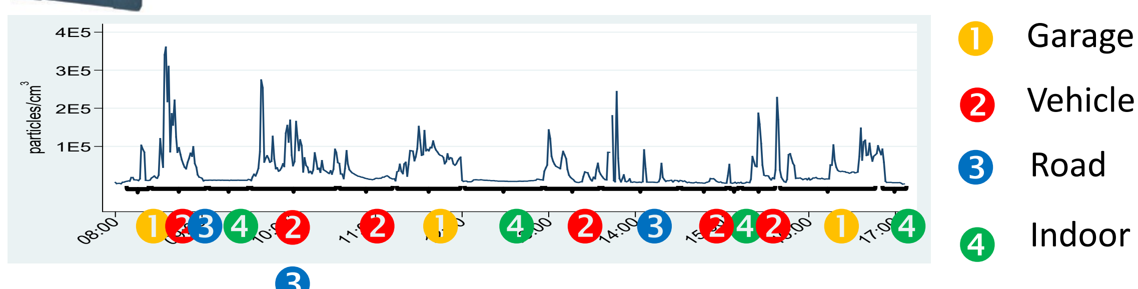
Sparse sensor network
(Nabel)

Expensive mobile
high fidelity equipment



Coarse models
(mesoscale = 1km²)

Personal exposure with
specialized punctual
studies



Explorative Efforts in Dense Sensing

- Examples of private sector initiatives

AirQualityEgg by Wicked Device;

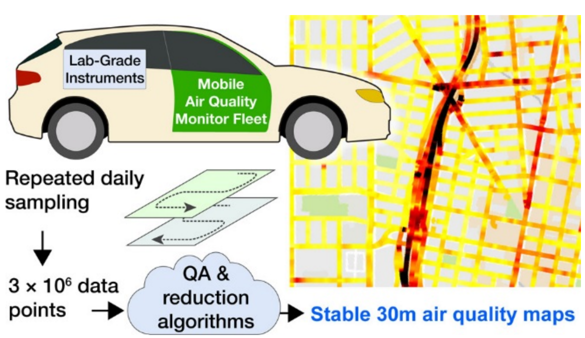
Laser Egg by Kai Terra;

Clarity Nodes by Clarity;

Airlib by Rimalu Technologies

- Examples of research initiatives

[Apte et al., *Environ. Sci. Technol., 2017]*

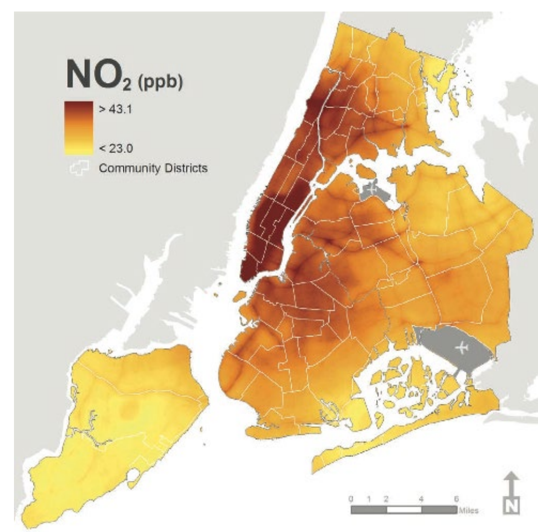


- Examples of city initiatives

Massive deployment of stations (150) at street-level (2008/2009 New York City Community Air Quality Survey);

Bloomberg Philanthropies with city of Paris: 150 Clarity nodes (PM 2.5/NO2) around schools with involvement of AirParif (2019)

Breathe London: 100 stationary nodes, two Google Street View cars, wearable sensors for chidren (2019)

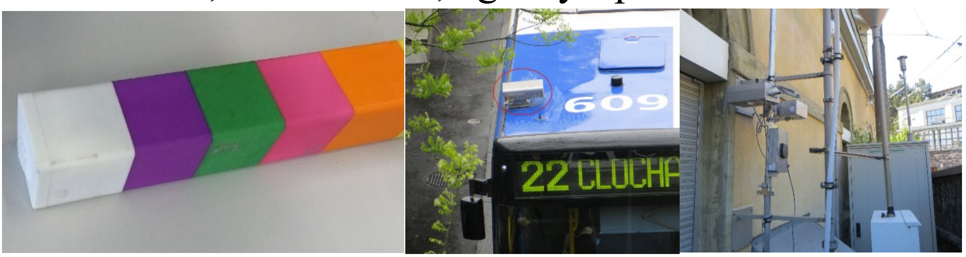


The OpenSense Project

OpenSense Vision

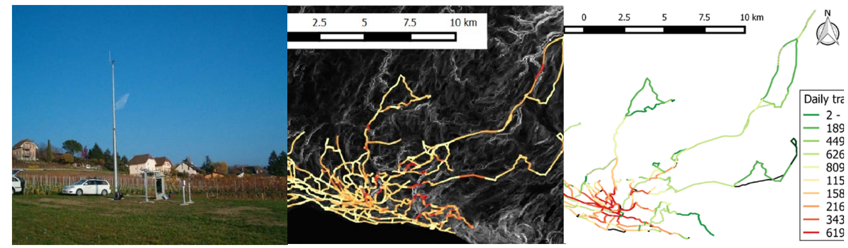
Measurement data

Citizen-, consortium-, agency-operated sensors



Explanatory Variables

Land-use, meteorology, traffic



Exposure information

Personal reccomendations, health studies, urban planning, crowdsensing

High-resolution pollution maps

Spatiotemporally flexible, modeling; emphasis on data-driven statistical modeling methods

OpenSense Sensing Platform (Lausanne Deployment)

- Mission: measure **gas-phase pollutants** (CO, NO_2, O_3, CO_2), **particulate matter** (PM), temperature and humidity

- Gases:
  - mix of small, relatively **low cost**, electrochemical, metal oxide, and optical sensors.
  - **slow response time; need re-calibration; cross-sensitive (low selectivity)**

- Particles:
  - physical metrics: Lung-Deposited Surface Area (LDSA)
  - **nanoscale sensitivity** (<100 nanometers)
  - **high cost**

- **Mobility energy**: leverage public transportation vehicles!
- **Connectivity**: leverage GPRS since no significant energy limitations!

Overview

Enable high spatio-temporal resolution monitoring of urban air quality through mobile wireless sensor networks.

System Design → Mobility Effects → Calibration → Mapping

System Design
- Modular & flexible
- Using low-cost sensors

Mobility Effects
- Slow sensor response
- Mitigation approaches

Calibration
- Novel model-based & mobility-aware approaches

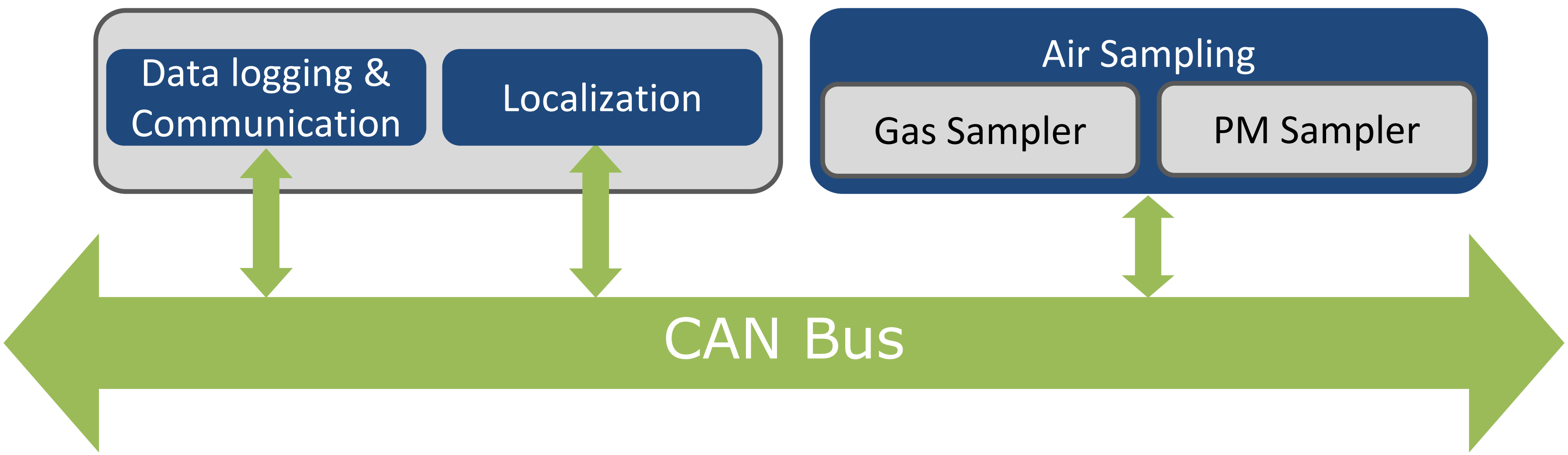
Mapping
- Novel statistical techniques
- Heterogeneous data sources

[Arfire, EPFL PhD thesis, 2016]

System Design → Mobility Effects → Calibration → Mapping

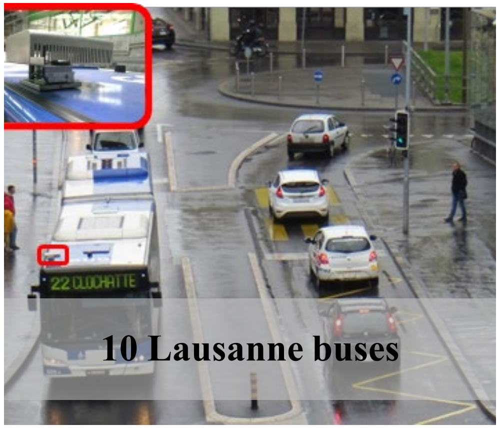
Contributors: Adrian Arfire, Emmanuel Droz, Alexander Bahr, Julien Eberle (LSIR-EPFL), Ali Marjovi, Christophe Paccolat

Sensor Node Design

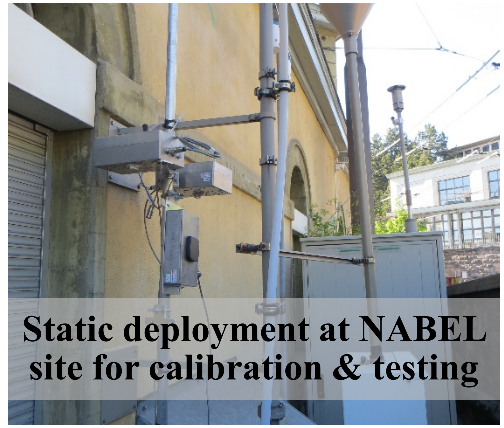


The Sensor Network

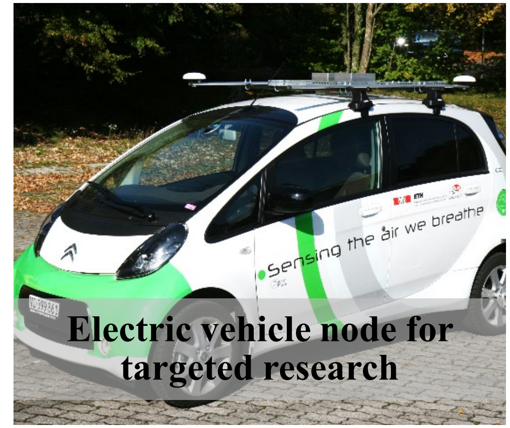
In the field



10 Lausanne buses

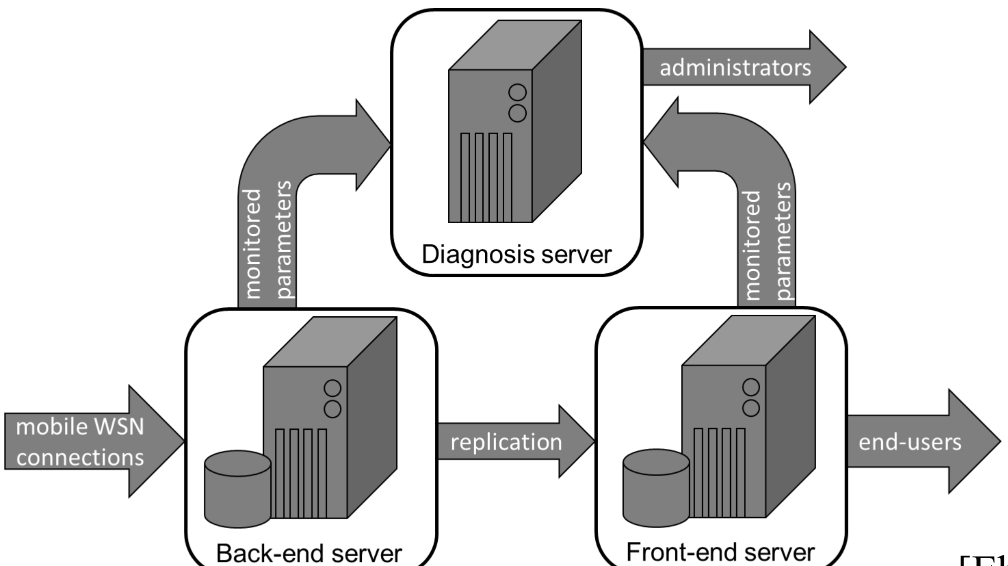


Static deployment at NABEL site for calibration & testing



Electric vehicle node for targeted research

Server-side



[Eberle, EPFL PhD thesis 2016]

System Performance

Data throughput

Deployment start: October 22, 2013 (~ 3 years), numerical values on Sep 28, 2016

Measurement	Sampling rate	# of measurements
LDSA (PM)	1 s	> 203 million
[CO, NO_2, CO_2]	5 s	> 101 million
[O_3, temp., RH]	5 s	> 71 million
GPS fix	1 s	> 325 million
[odometer, accelerometer]	0.25 s	> 1352 million
vehicle context info	event-driven	> 14 million

- [Arfire et al., in preparation]

System Design → Mobility Effects → Calibration → Mapping

Contributors: Adrian Arfire, Ali Marjovi

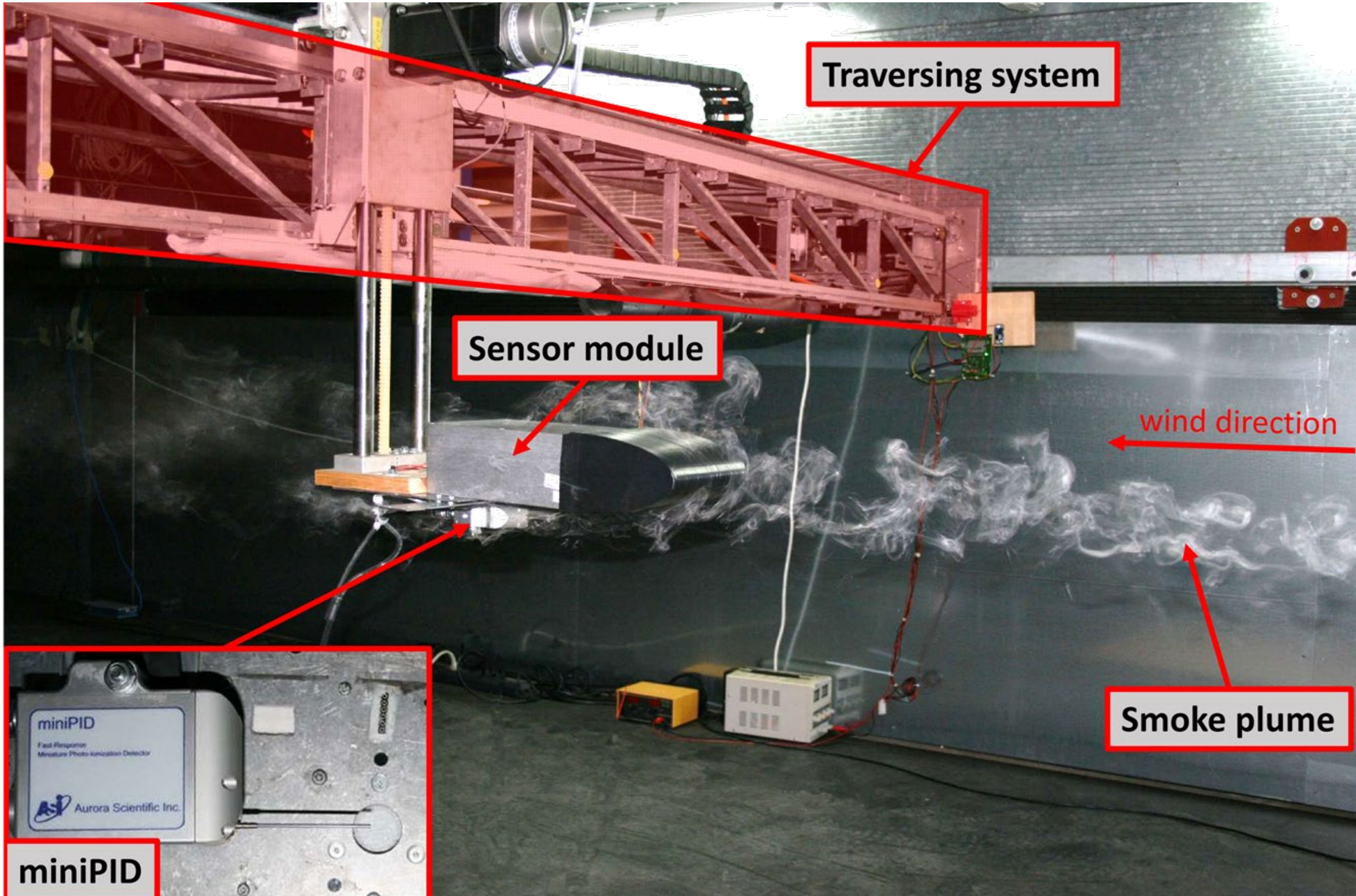
Mobility Effect

- Except for work in robot olfaction, largely unaddressed

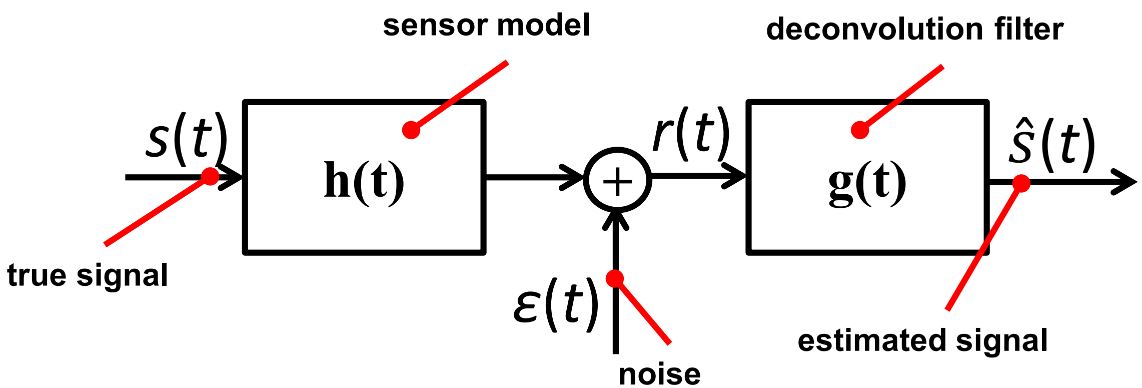
Strategies:

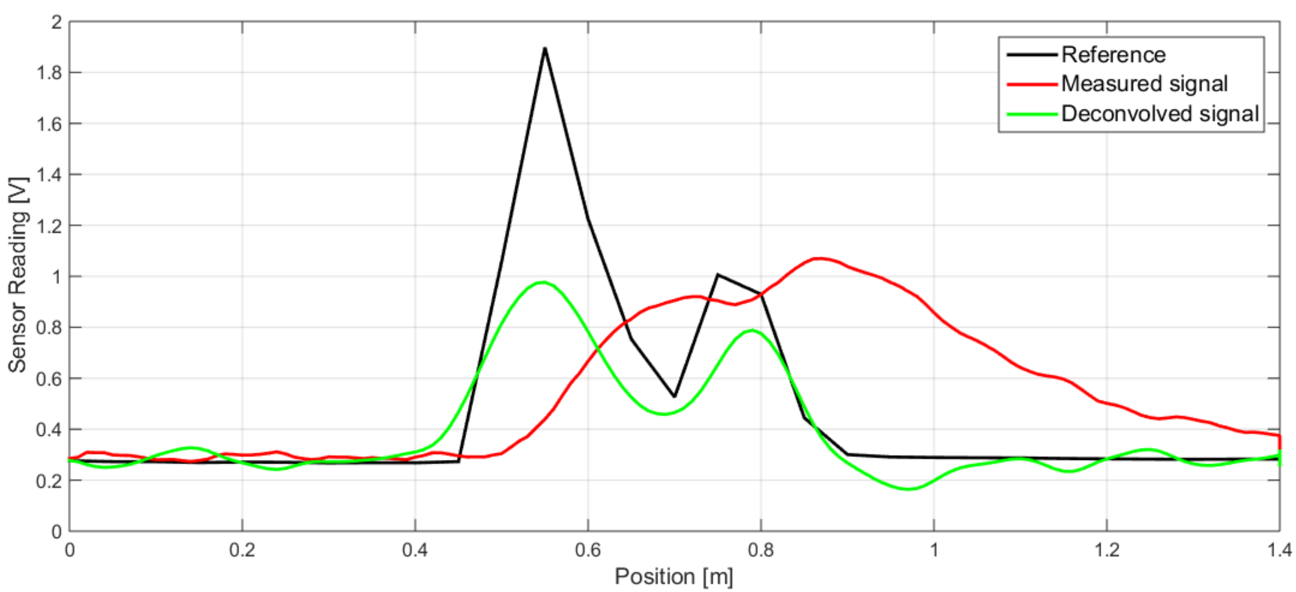
- Limiting robot velocity
- Cycling between movement & stationary measurement
- Customized **air sampling systems**

Experimental Set-up



Signal Reconstruction through Deconvolution

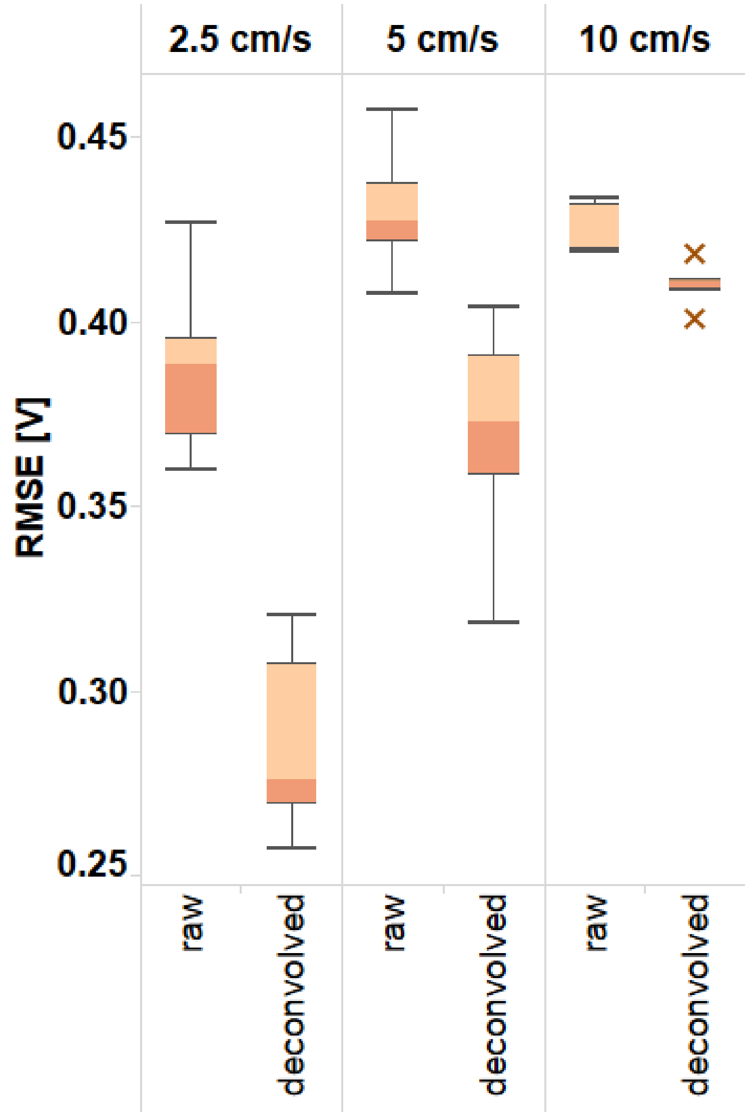




Signal Reconstruction through Deconvolution

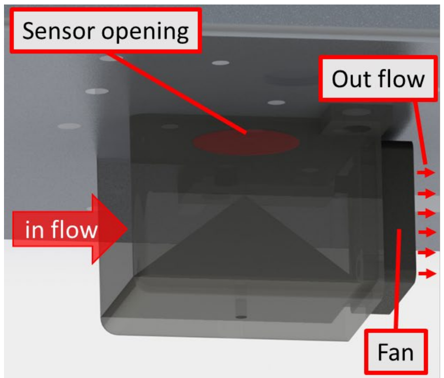
Results

- Consistent performance improvement
- Reduction of RMSE drops as the speed increases (SNR decreases)

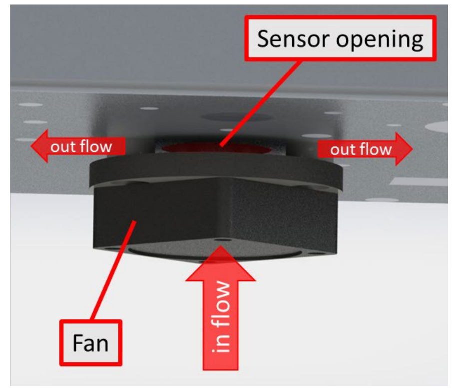


Active Sampling System Design

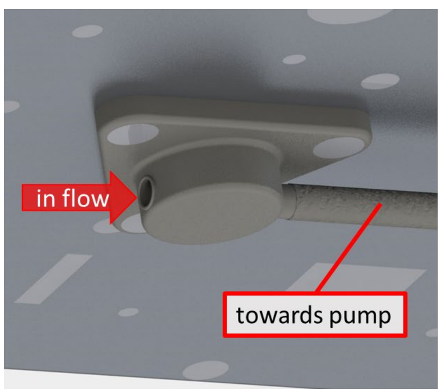
Actuation: axial fans, diaphragm pumps



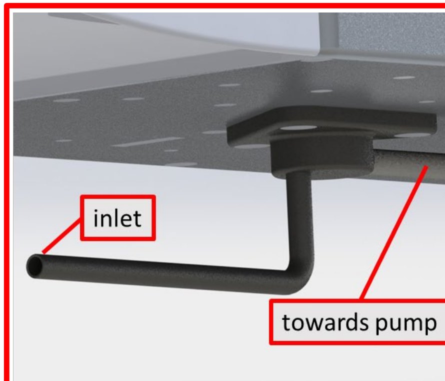
Lateral-flow



Normal-flow



Leveled-inlet

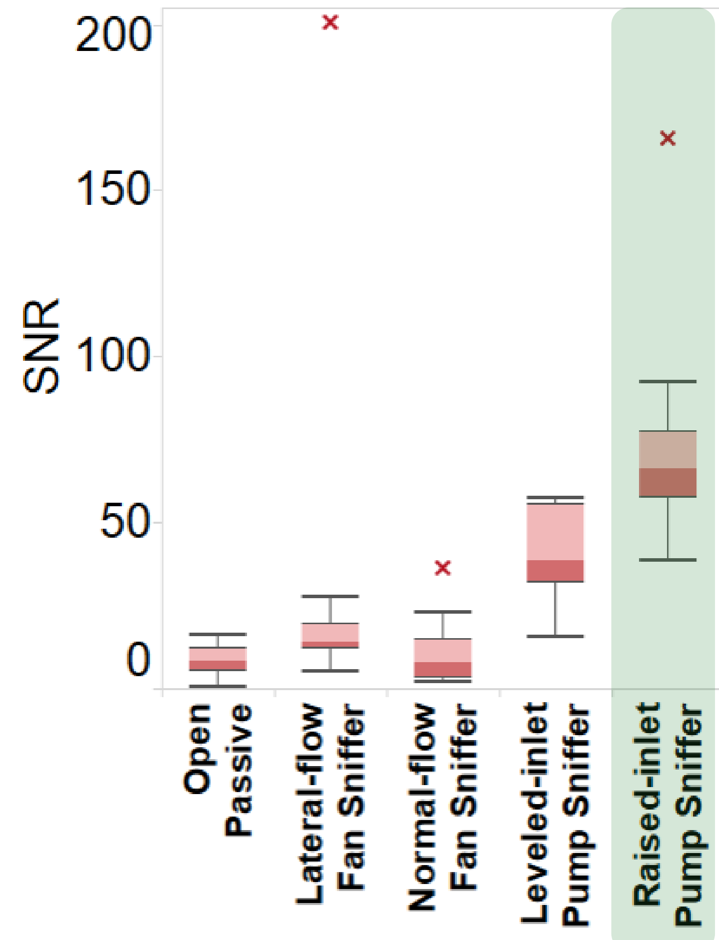


Raised-inlet

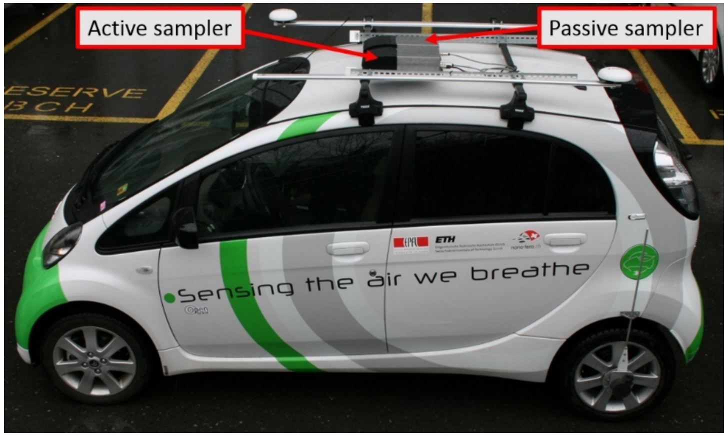
Air Sampling System Comparison

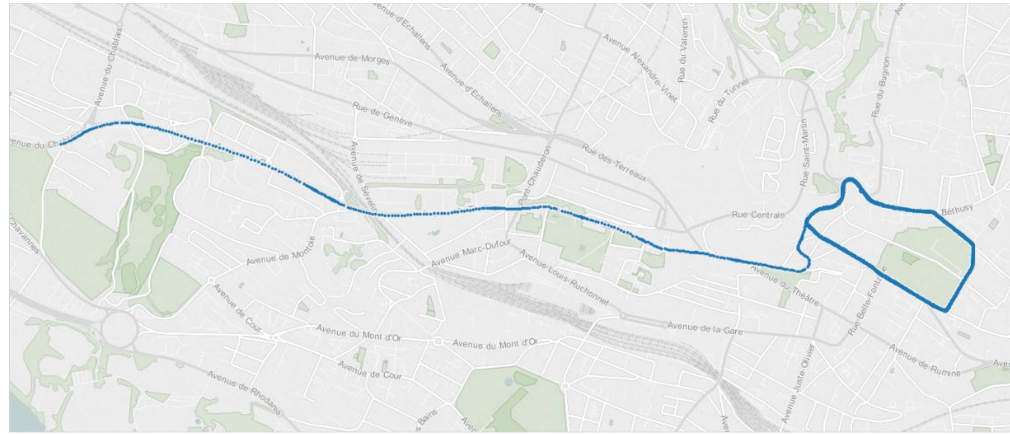
Results

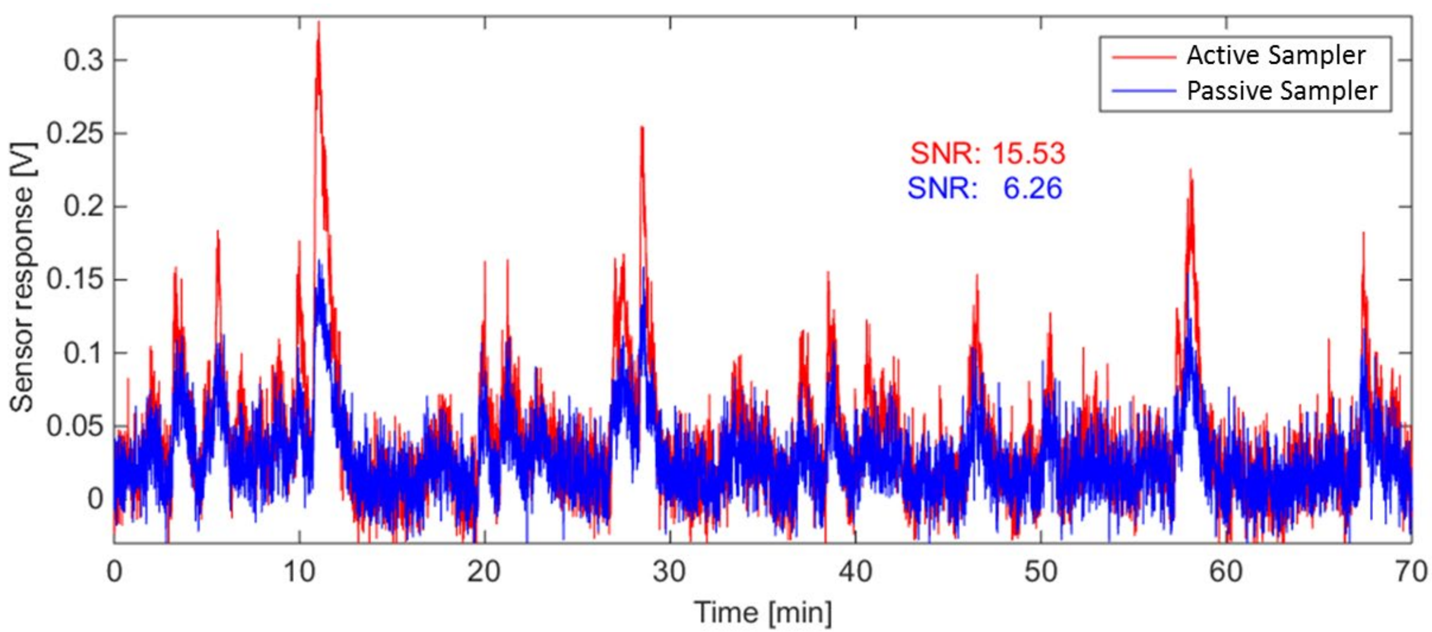
- Best performance: **pump-based sniffers**



Outdoor Experimental Validation







[Arfire et al., AIM 2016, EWSN 2016]

System Design → Mobility Effects → Calibration → Mapping

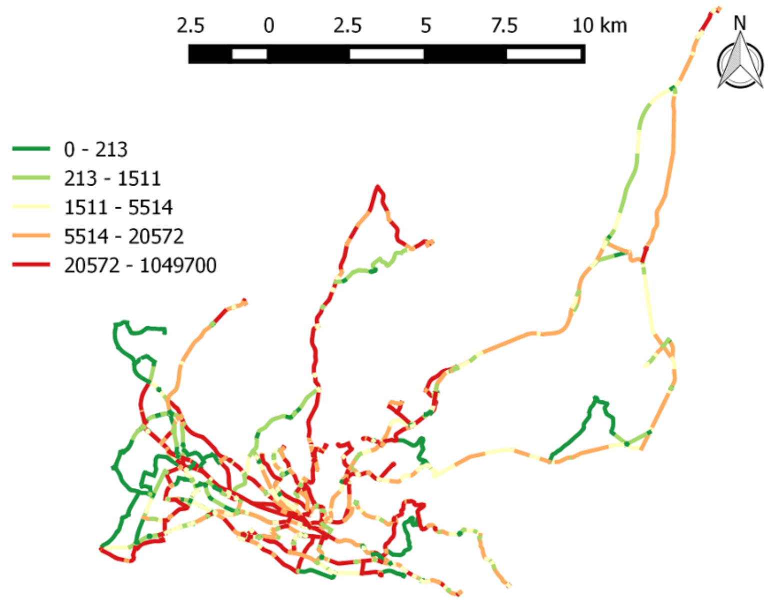
Contributors: Ali Marjovi, Adrian Arfire, Loïc Frund, Fabrizzio Gonzales, Thomas Coral, Jonathan Giezendanner

Mapping Problem

- LDSA data is sparse
- Coverage of sensors is incomplete and dynamic

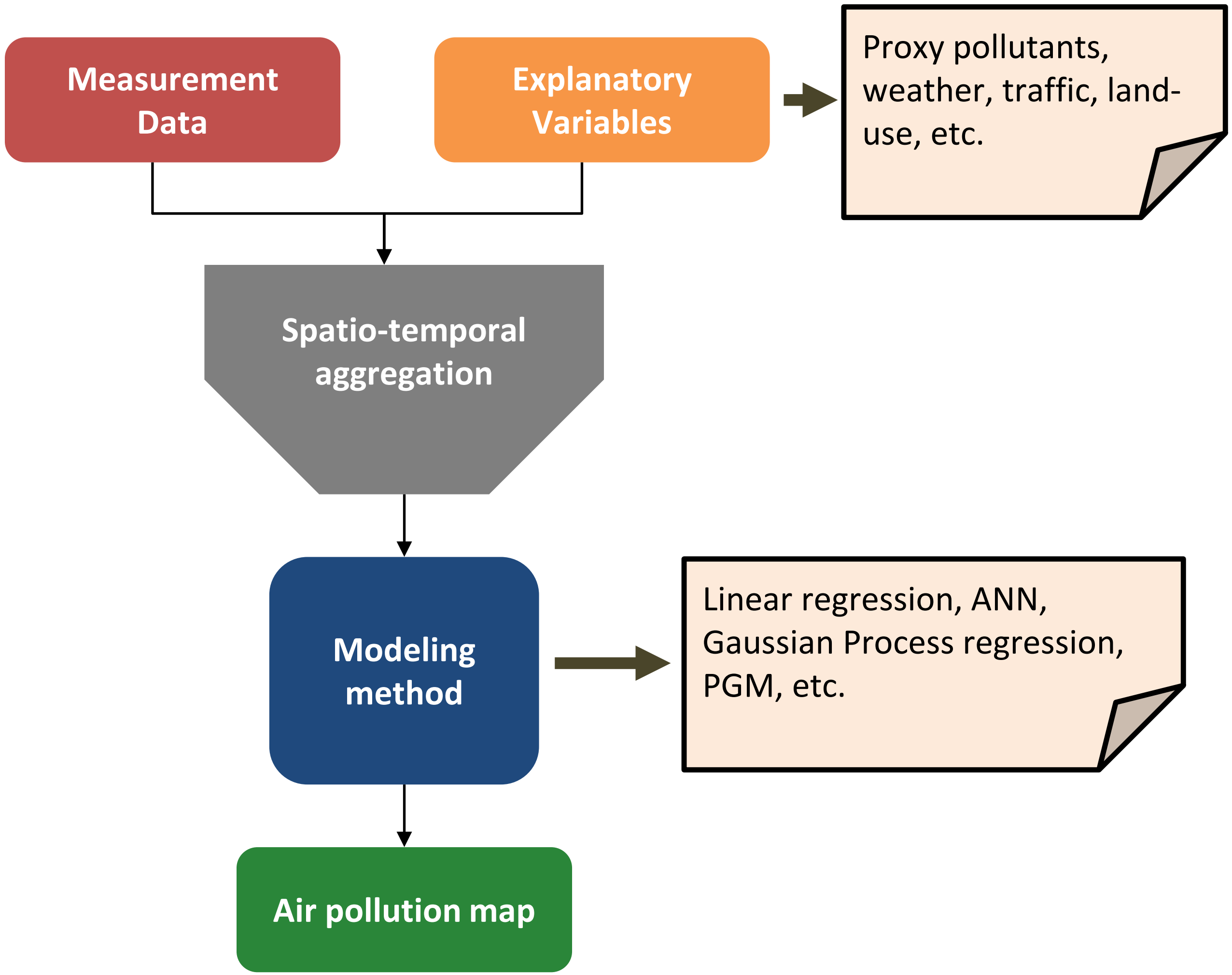
- Generating complete maps is a challenge.

Solution:
- Other sources of data is required
- Models are required to estimate the LDSA in locations/times of interest

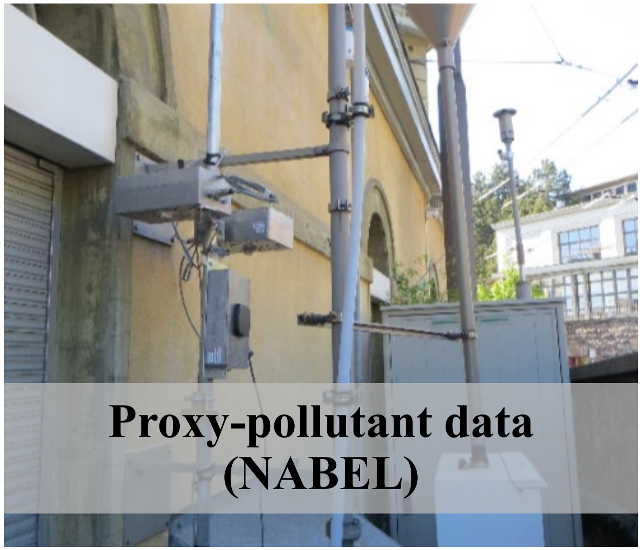


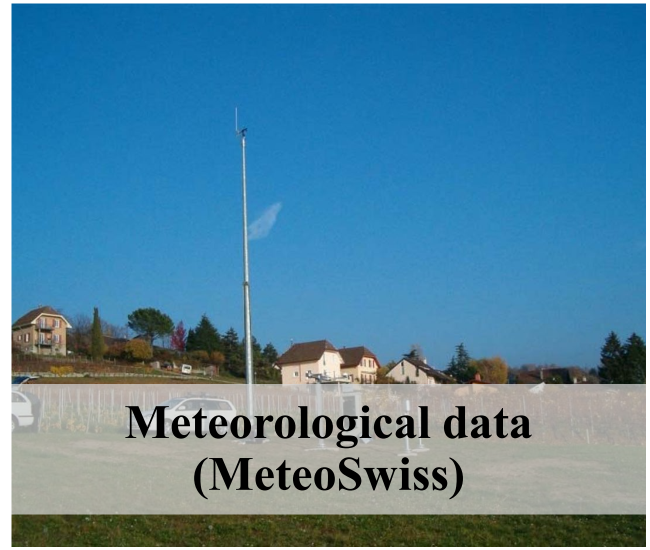
Number of LDSA measurements per street segment during one year.

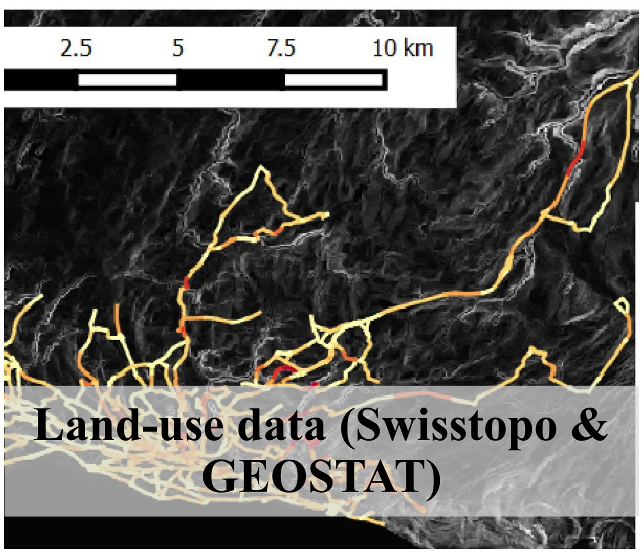
Statistical Modeling - Overview



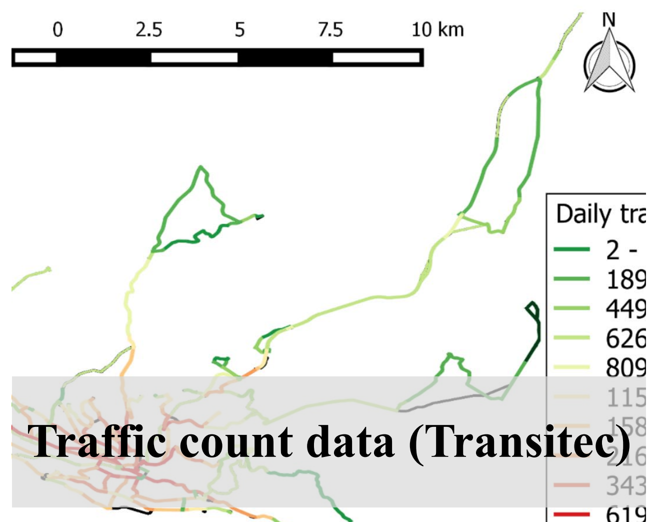
Explanatory Variables


Proxy-pollutant data (NABEL)


Meteorological data (MeteoSwiss)



Land-use data (Swisstopo & GEOSTAT)



Traffic count data (Transitec)

Modeling Methods

Local models

Basic Log-Linear (BLL) regression

$$\log(L_m) = \alpha_0 + \sum_{i=1}^{9} \alpha_i \cdot \log(v_i)$$

Network-based Log-Linear (NLL) regression

- Dependency network – measurement correlation & complementarity

$$\log(L_{S_m}) = \alpha_0 + \sum_{i=1}^{9} \alpha_i \cdot \log(v_i) + \sum_{[m-n]\in E} \alpha_n \cdot \log(L_{S_n})$$

Global models

Basic Log-Linear with Land-Use (BLL-LU) regression

$$\log(L_{S_m}) = \alpha + \sum_{i=1}^{9} \beta_i \cdot \log(v_i) + \sum_{i=1}^{17} \gamma_i \cdot \log(U_{i,S_m})$$

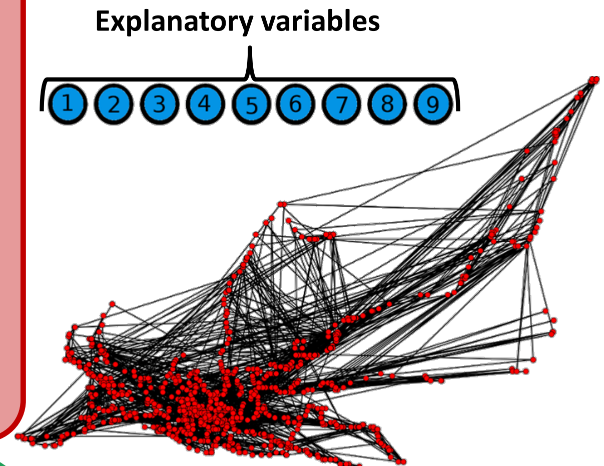
Land-Use Network-based Log-Linear (LU-NLL) regression

- Dependency network – land-use data

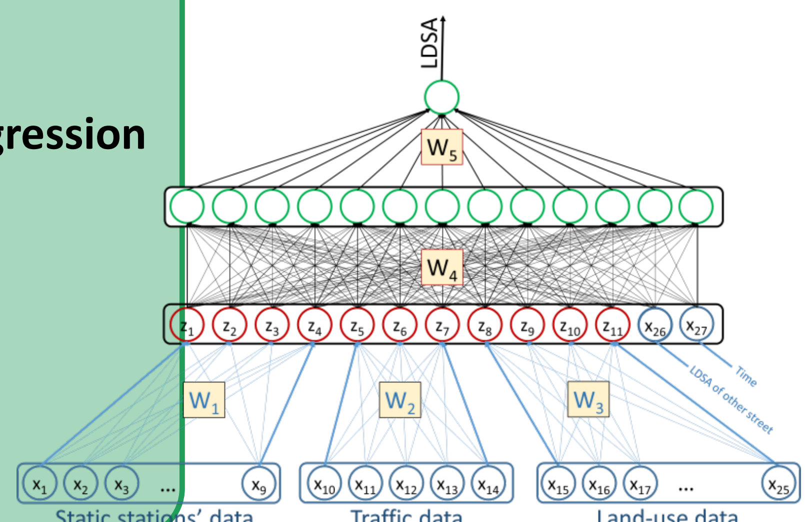
$$\log(L_{S_m}) = \alpha + \sum_{i=1}^{9} \beta_i \cdot \log(v_i) + \sum_{i=1}^{17} \gamma_i \cdot \log(U_{i,S_m}) + \sum_{[m-n]\in E} \delta_n \cdot \log(L_{S_n})$$

Deep Learning Model (DLM)

- ANN training technique



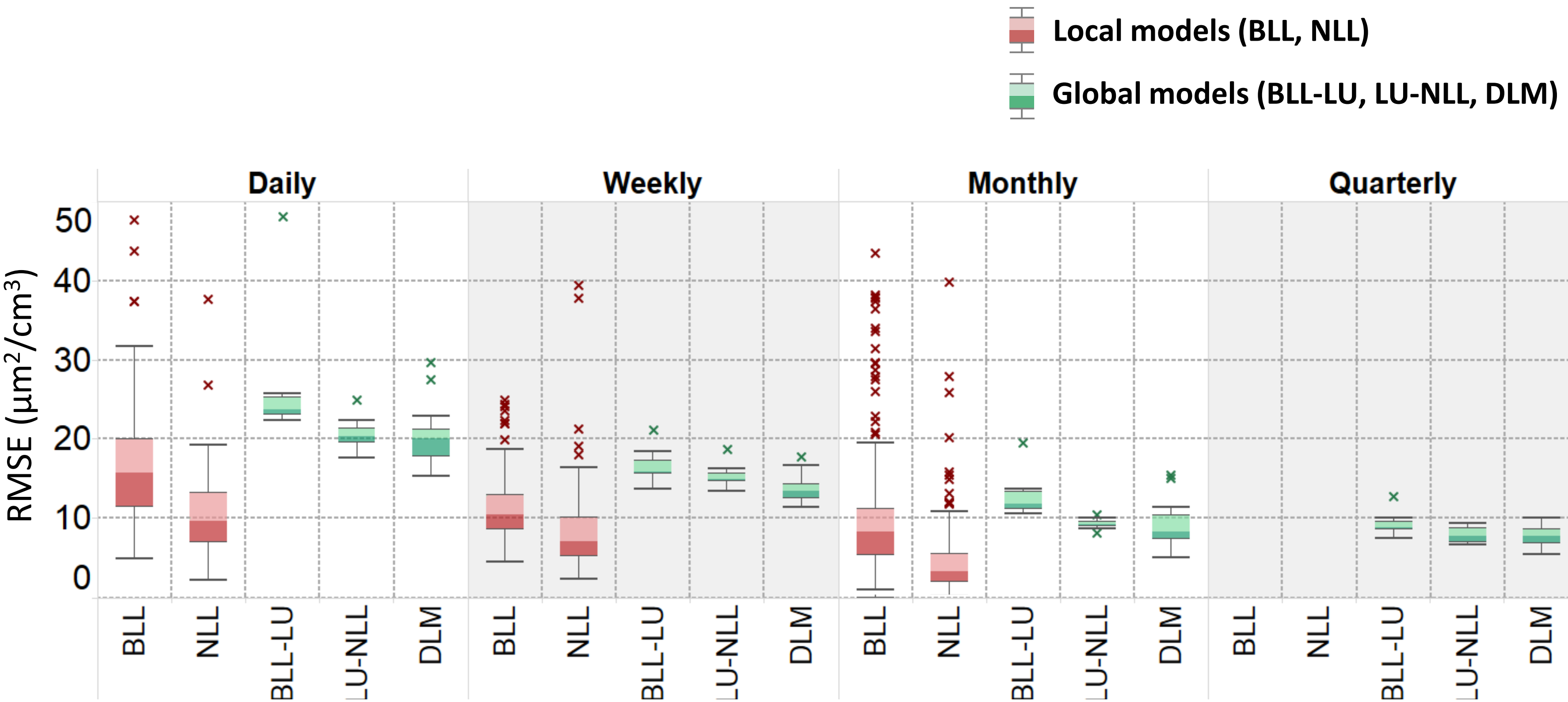
NLL dependency network



ANN structure for DLM method

Performance

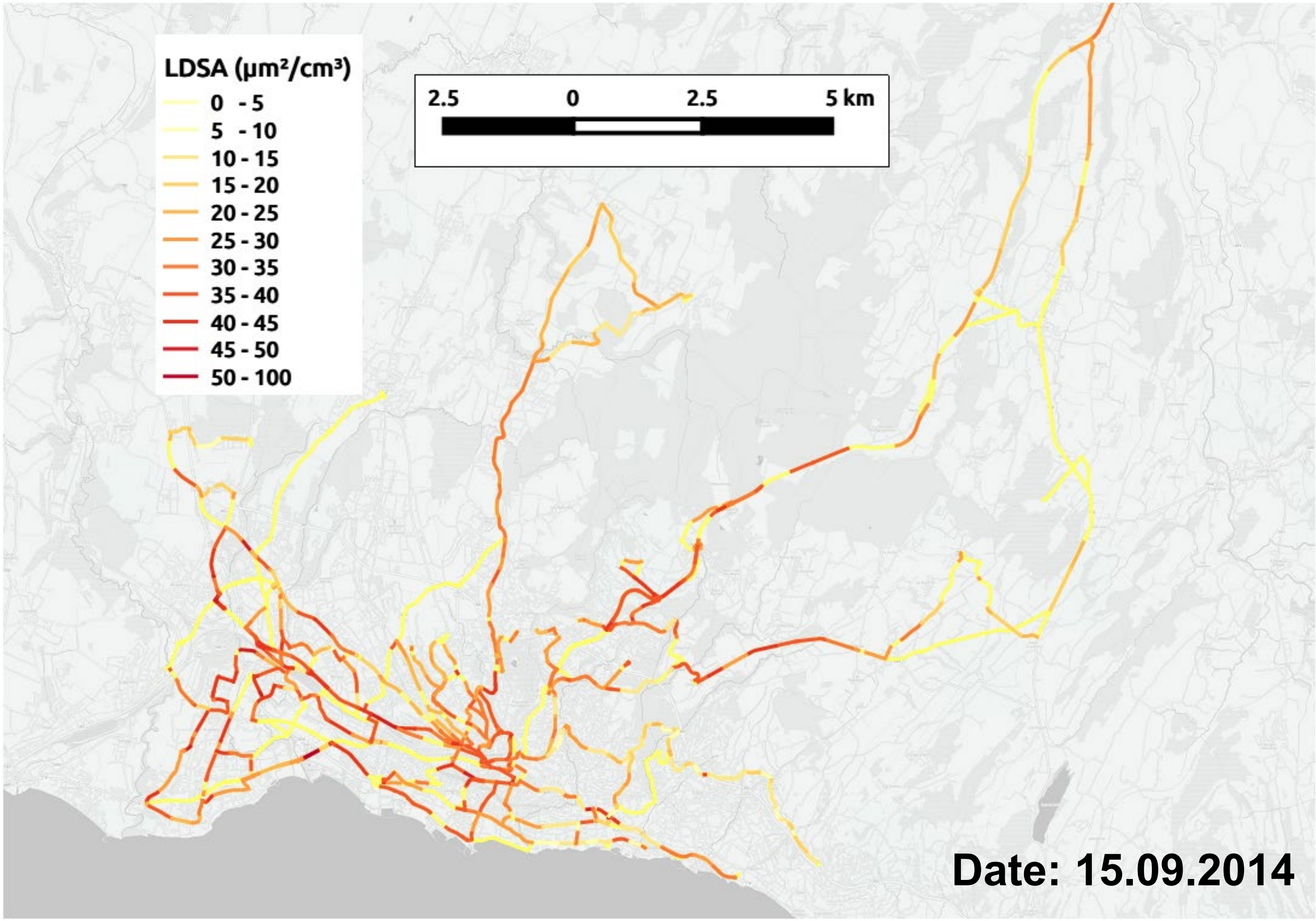
Results



[Marjovi et al., DCOSS 15]
[Marjovi et al., EWSN 17]

Pollution Map Example

Coverage extended to the regions where both land-use and traffic data is available.



Conclusion

Take Home Messages

- The area of sensor systems and sensor networks is booming for all sort of applications
- A lot of these applications are directly concerning the natural and built environment
- They are characterized by various degree of mobility (e.g., static, manually deployable, parasitic mobility)
- Totally new, unprecedented, and often distributed instruments are developed in the research labs and are becoming available on the market via various start-ups
- Intelligent instruments are very powerful and characterized by an increased software complexity which offer new opportunities in terms of customization, automation, etc.

Additional Literature – Week 12

Pointers

- OpenSense: http://opensense.epfl.ch
- Breathe London: https://www.breathelondon.org/

Articles

- B. Maag, O. Saukh, D. Hasenfratz, L. Thiele, "Pre-Deployment Testing, Augmentation and Calibration of Cross-Sensitive Sensors", *Proc. of the International Conference on Embedded Wireless Systems and Networks*, February 2016, Graz, Austria, pp. 169-180.
- D. Hasenfratz, O. Saukh, C. Walser, C. Hueglin, M. Fierz, T. Arn, J. Beutel, and L. Thiele, "Deriving high-resolution urban air pollution maps using mobile sensor nodes," *Pervasive and Mobile Computing*, vol. 16, pp. 268–285, 2015.
- Arfire A., Marjovi A., and Martinoli A., "Mitigating slow dynamics of low-cost chemical sensors for mobile air quality monitoring sensor networks," *Proc. of the International Conference on Embedded Wireless Systems and Networks*, February 2016, Graz, Austria, pp. 159–167.