Machine Learning for 5G and Beyond: Towards Reliable and Efficient Reconstruction of Radio Maps

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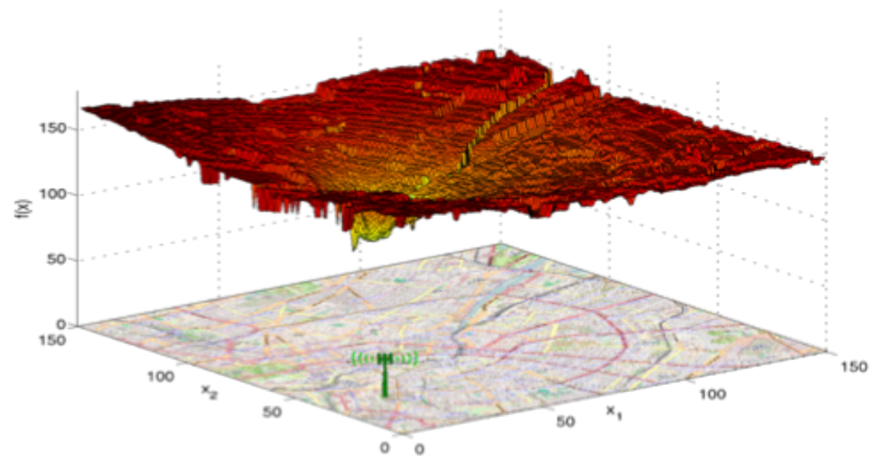
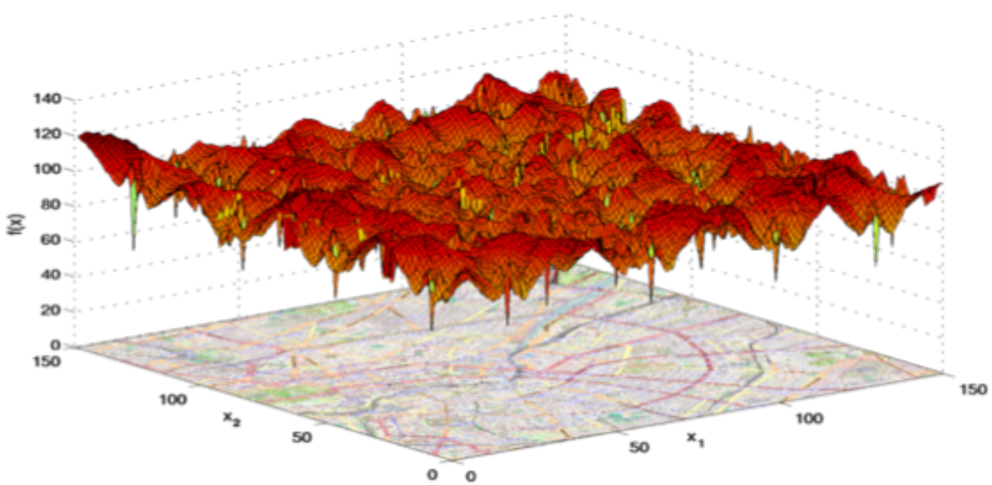
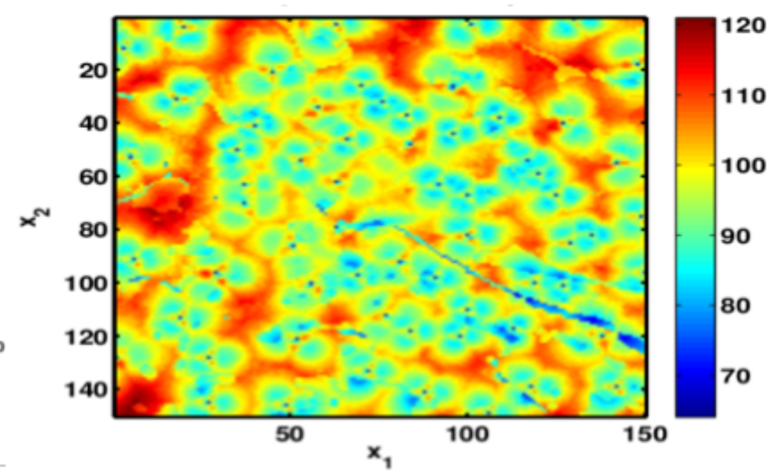
Introduction

- A radio map is an (unknown) function that relates a geographic location to some radio system parameter (e.g. path-loss, capacity, QoS etc).
- **Goal**: Reconstruction of radio maps in an online fashion from user measurements





2D view:

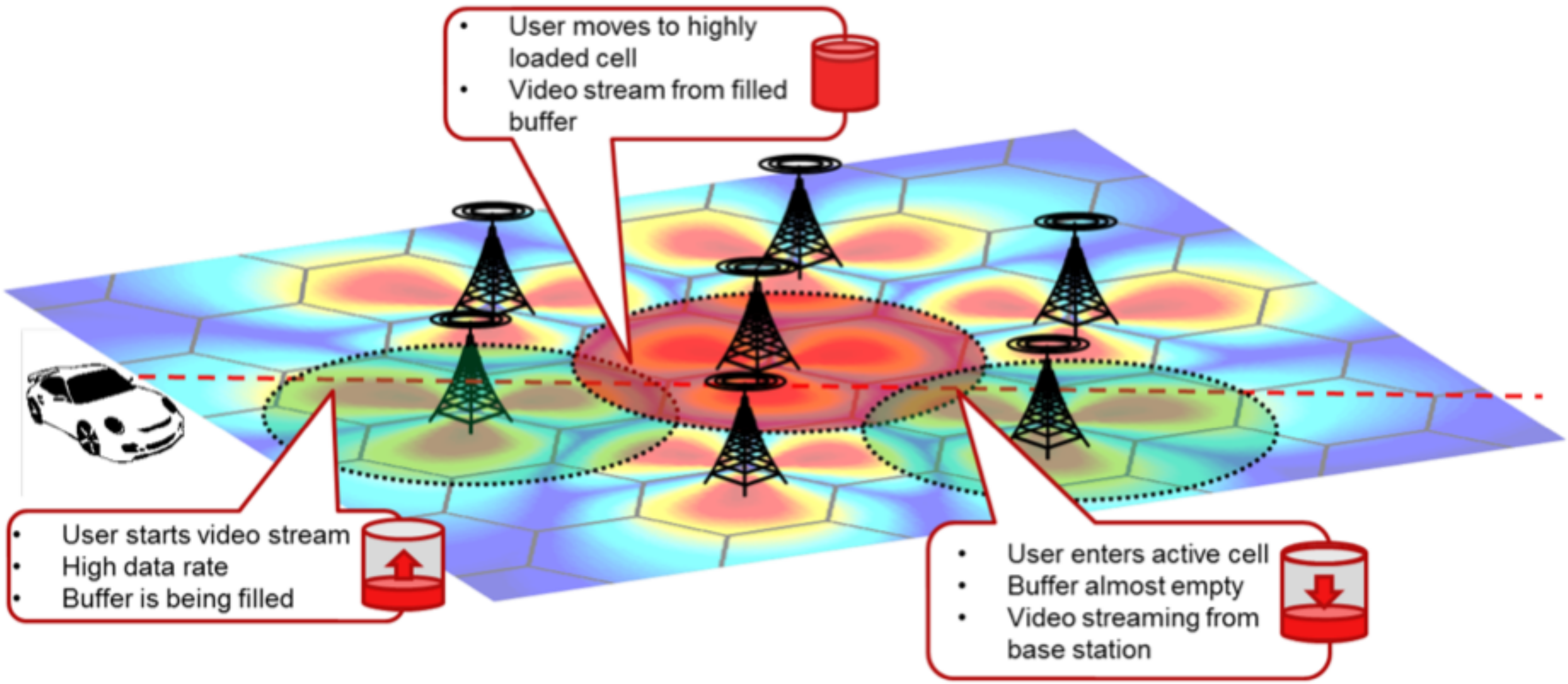


What are the challenges & opportunities?

- High mobility
  ➔ changes in network topology
  ➔ **wireless links exhibit ephemeral and dynamic nature**
  ➔ Non-stationarity (and non-ergodicity)
- Noisy capacity-limited transmission exposed to interference
  ➔ wireless channel is error-prone and highly unreliable
- Stringent requirements of many 5G applications
- Data is distributed at different locations
- Models, context information and expert knowledge are available
- There is a lot of structure in the channel, signals and functions
- Low-complexity, low-latency implementation

ML for Reconstruction of Capacity Maps

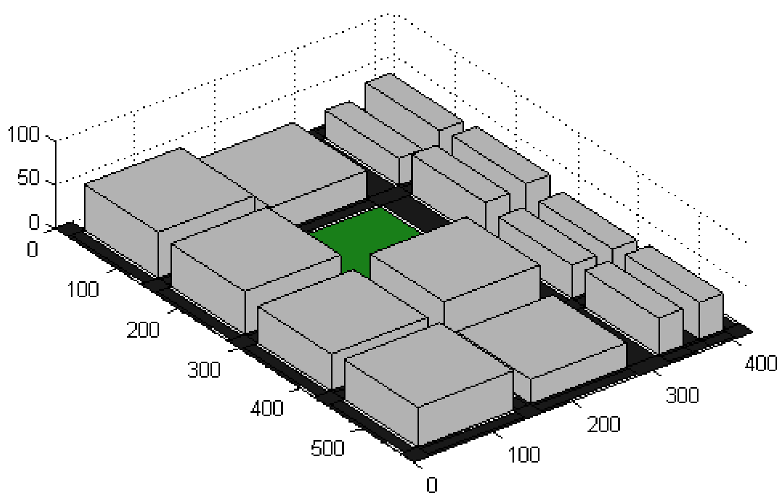
- Adaptive learning of long-term capacity maps



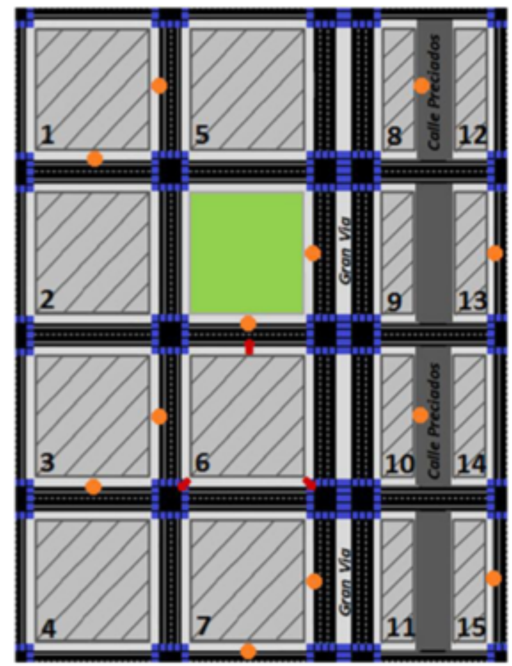
Madrid Scenario

Madrid grid environmental model

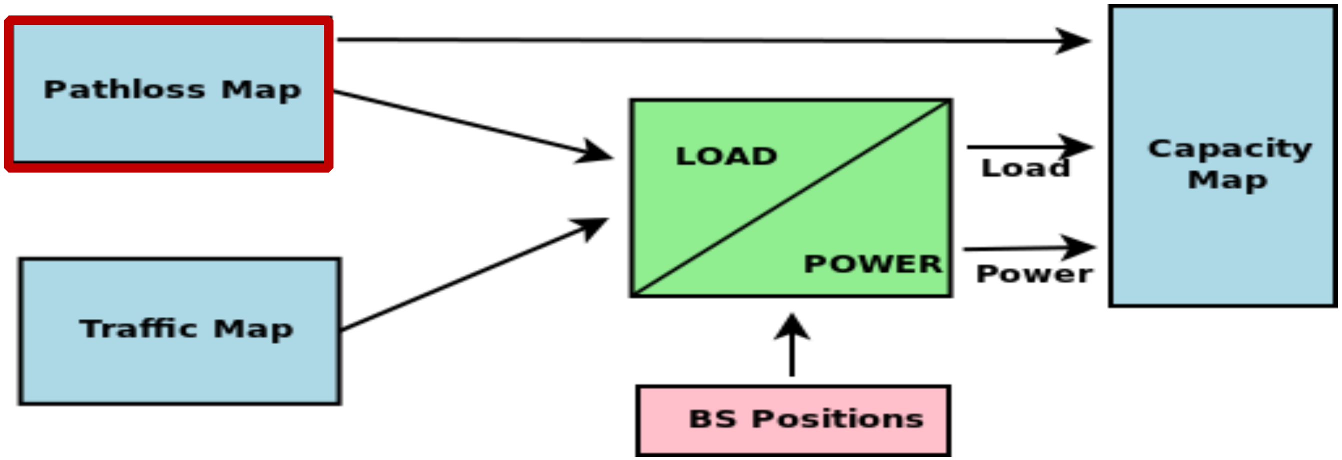
- Model of a city layed out on a grid
- Raytracing data from the METIS project
- Three different heights (floors)
- Wrap-around model to remove edge effects

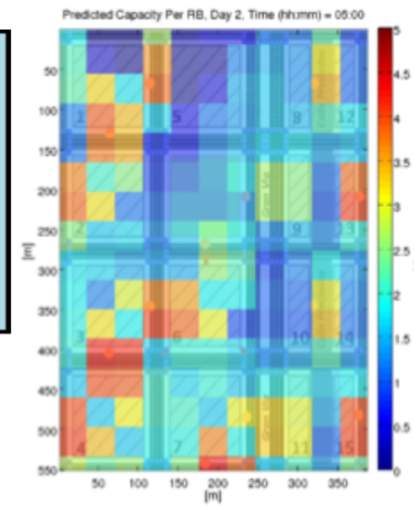


Source: METIS Deliverable ICT-317669-METIS/D6.1



Learning Capacity Maps: Key Ingredients





- **Pathloss map**: adaptive projected **sparse-aware multi-kernel approach**

Kasparick M., R. L. G. Cavalcante, S. Valentin, S. Stanczak, and M. Yukawa, "Kernel-Based Adaptive Online Reconstruction of Coverage Maps with Side Information," IEEE Transactions on Vehicular Technology, vol. 65, no. 7, pp. 5461-5473, July 2016

Learning of Pathloss Maps

Each base station has access to pathloss measurements (that arrive over time) and maintains prediction of pathloss in its area of coverage

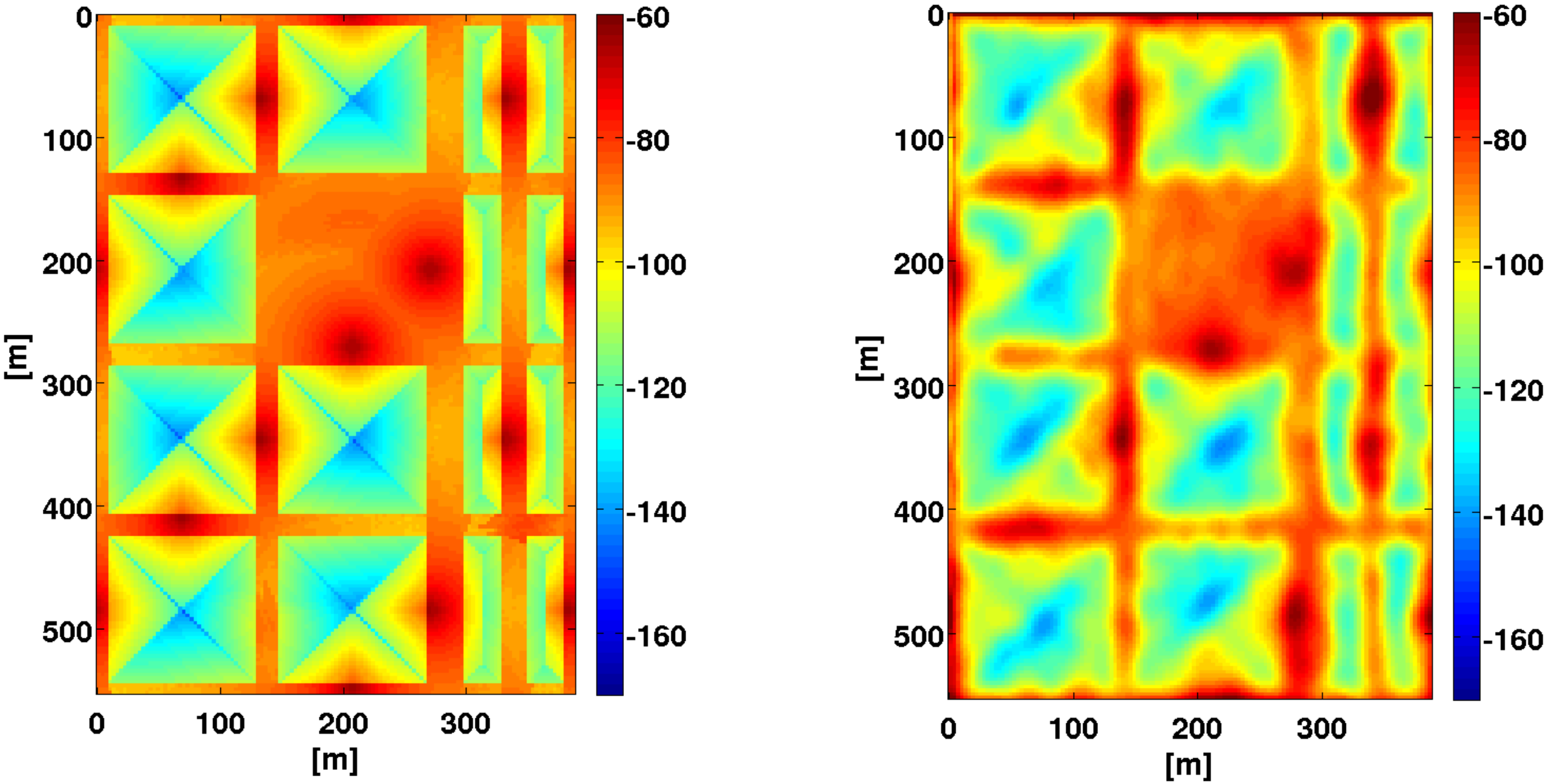
Whenever new measurement arrives, the base station updates its current approximation of the unknown pathloss function

Measurements may contain errors that are not uniformly distributed

Requirements:

- **High estimation accuracy** despite the lack of measurements in som e areas
- **Adaptivity and good tracking capabilities**: Online learning based on measurements
- **Low Complexity**: Measurements are processed in real time
- **Robustness**: Error tolerance with respect to reported measurements

Learning of Pathloss Maps



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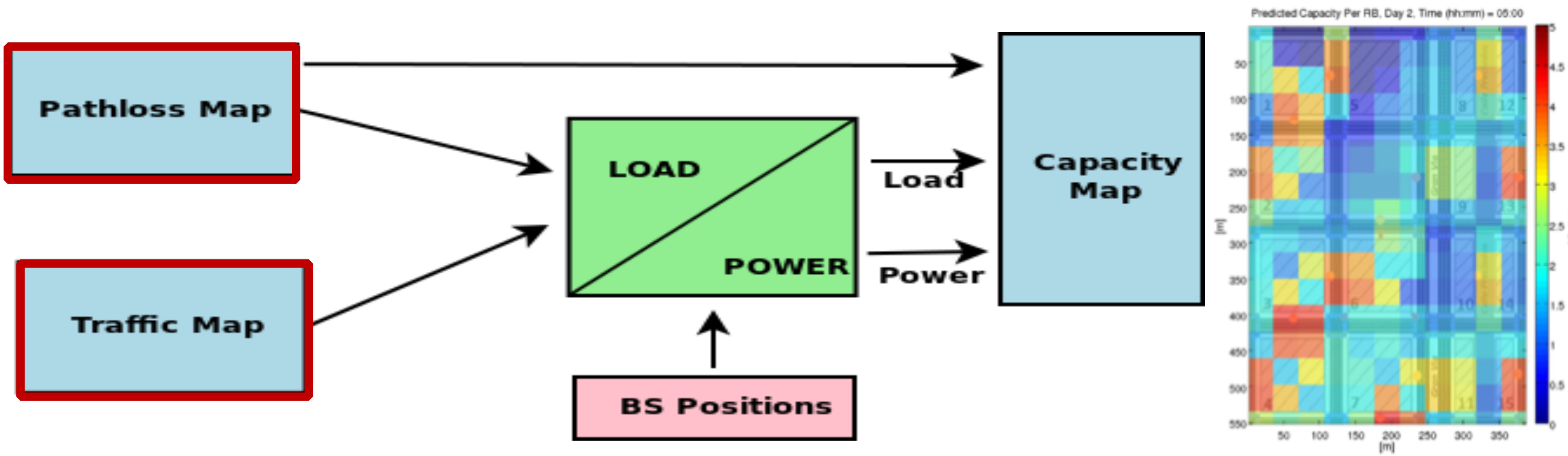


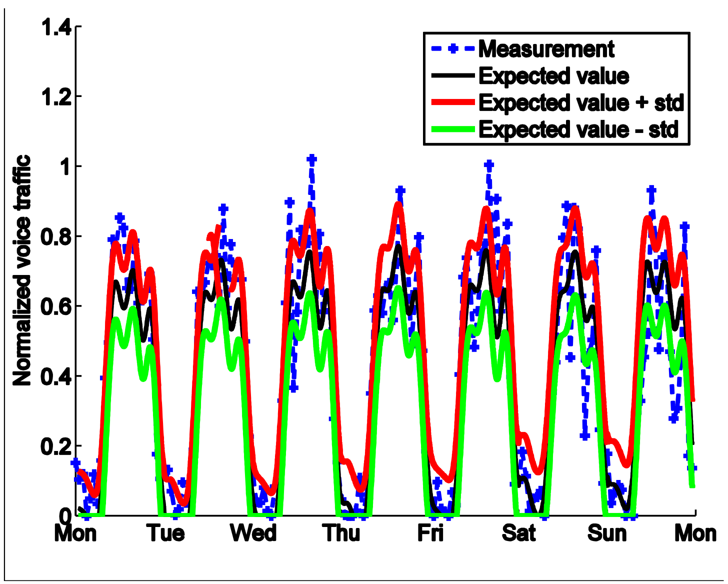
- **Pathloss map**: adaptive projected sparse-aware multi-kernel approach
- **Traffic map**: Gaussian processes, Quantile estimation, context information

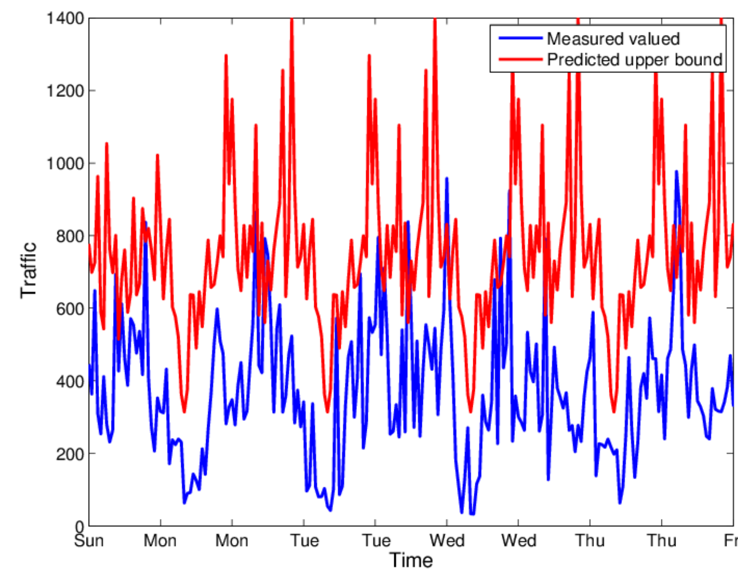
R. L. G. Cavalcante, et.al., "Toward Energy-Efficient 5G Wireless Communications Technologies: Tools for decoupling the scaling of networks from the growth of operating power," n IEEE Signal Processing Magazine, Nov. 2014.

Real Network: Learning Data Traffic

Objective: Predict the traffic demand in a given area by using observed time series and **contextual information** (e.g., day of the week, holidays)

- Learn from the environment
- Good predictive power forecasts with confidence intervals
- **Do not try to learn too much!**

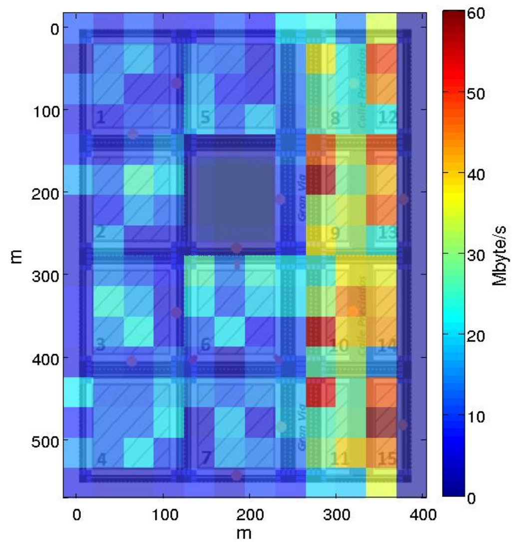


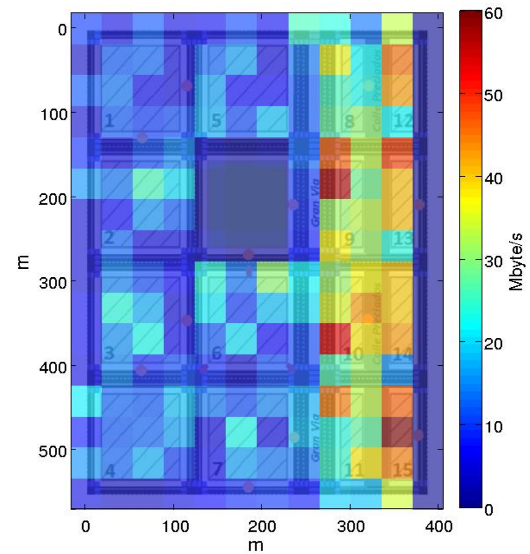


Source: R. L. G. Cavalcante, et.al., "Toward Energy-Efficient 5G Wireless Communications Technologies: Tools for decoupling the scaling of networks from the growth of operating power," n IEEE Signal Processing Magazine, Nov. 2014.

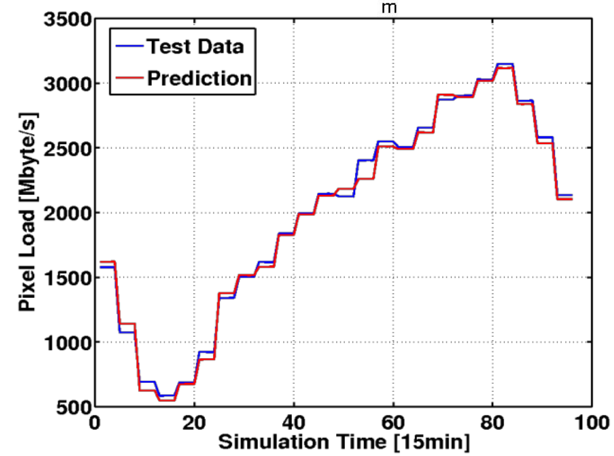
Learning Data Traffic

Simulation Parameter	Value
Size of test point	35 m×35 m
Total number of test point	176
Amount of training data	4 days
Amount of test data	1 day
Time granularity	15 minutes
Type of Kernel	composite (22)
Kernel period	1 day
Kernel parameter	1e-6
Sparsification parameter	0.99

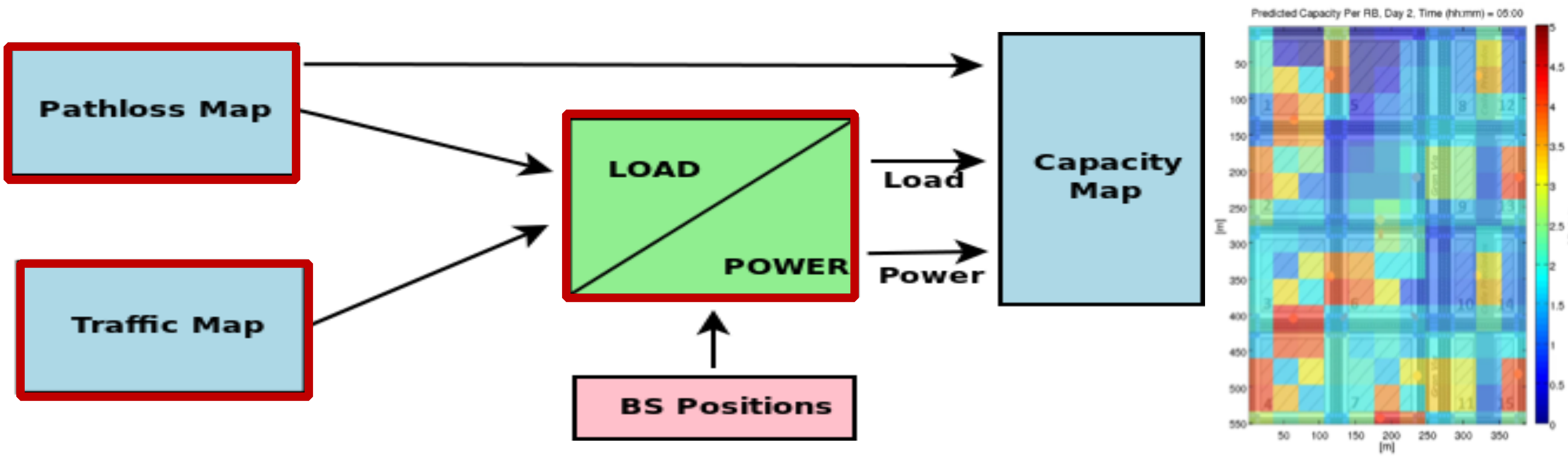




- **Above**: Traffic maps for a particular time point, after training phase of 4 days
- **Right**: Aggregated traffic demand prediction for 1 day, after 4 days of training



Learning Capacity Maps: Key Ingredients



- **Pathloss map**: adaptive projected sparse-aware multi-kernel approach
- **Traffic map**: Gaussian processes, Quantile estimation, context information
- **Load estimation**: hybrid-driven methods

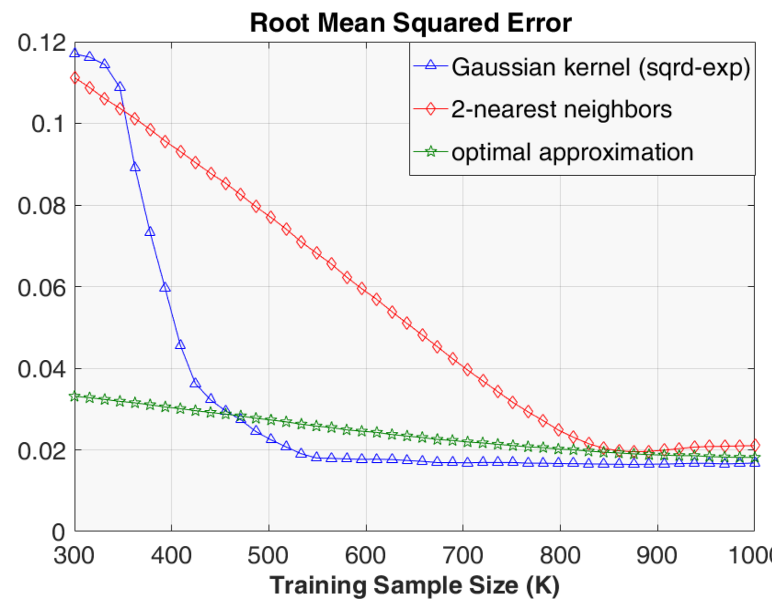
D. A. Awan, R. L. G. Cavalcante, and S. Stanczak, ``A robust machine learning method for cell-load approximation in wireless networks,´´ arXiv:1710.09318, 2017

Learning Load Maps

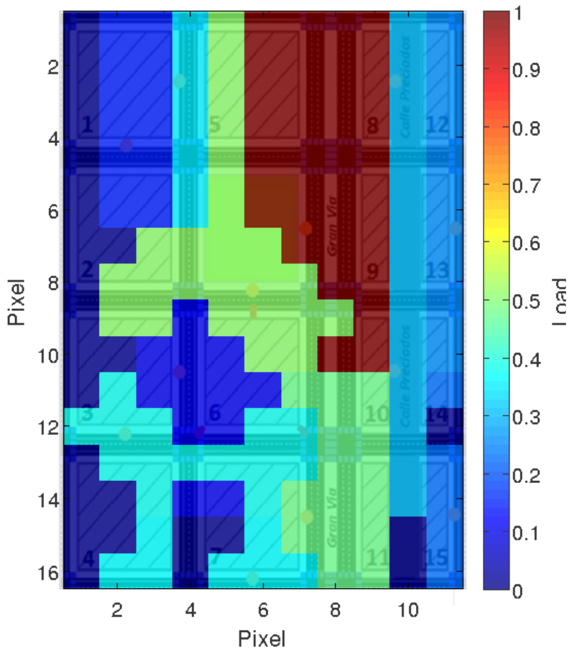
Objective: Given a power allocation for cells and the traffic demand for users, what is the load at each cell (fraction of the used resources)?

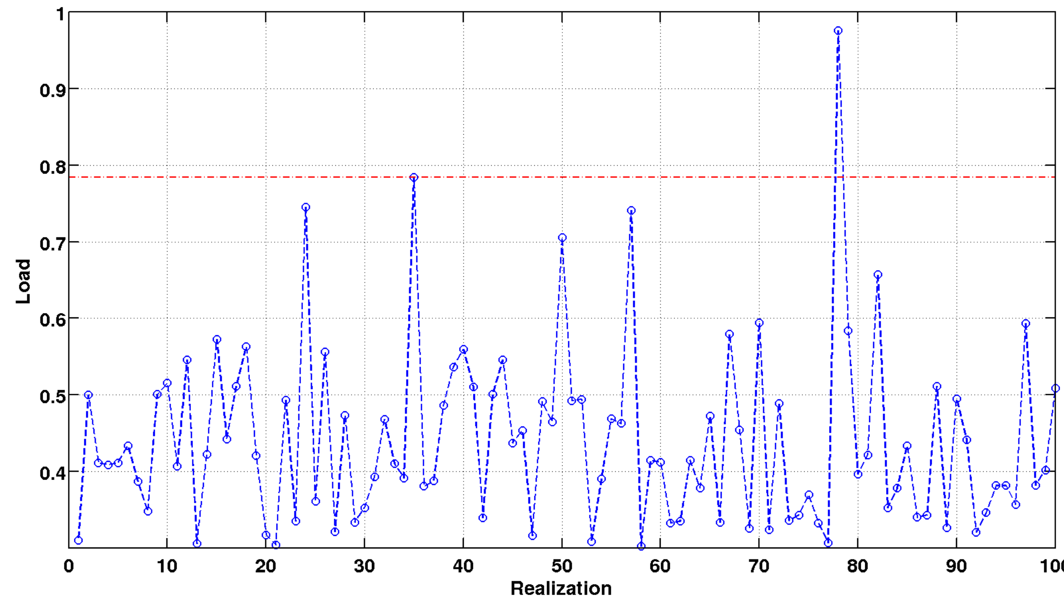
Challenge: The mapping relating rate to load is highly dynamic and nonlinear owing to the interference ➔ **training must be short**

- The rate-load mapping has a **rich structure** (e.g., monotonicity) that is hard to exploit in typical machine learning tools
- New **hybrid-driven methods**: more robust and optimal, in a well-defined sense, in uncertain environments



Learning Load Maps

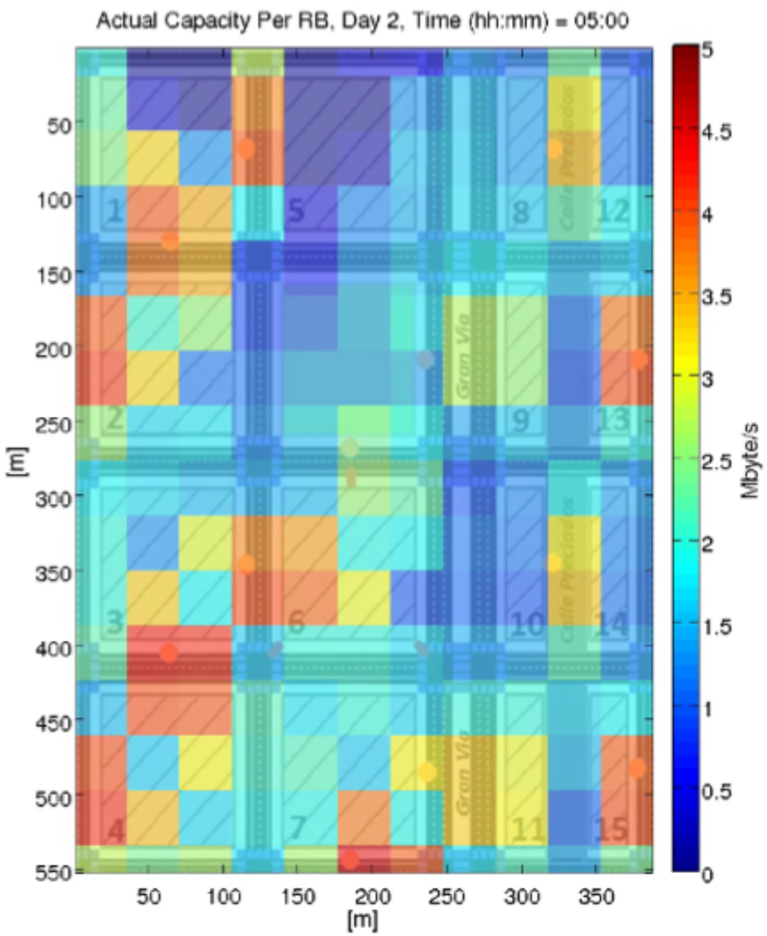


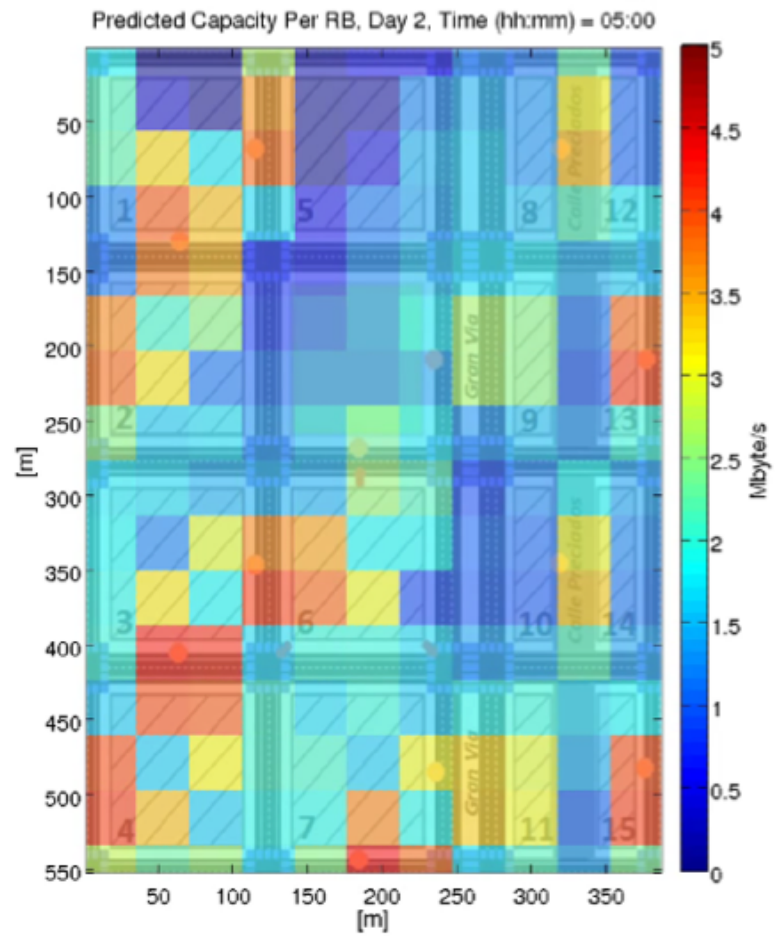


We combine the tools with statistical methods to obtain probabilistic bounds

- Serve as a basis for network optimization decisions
- Example: operator is interested in knowing if particular configuration will be sufficient to guarantee a certain maximum load with a given probability

Learning Capacity Maps





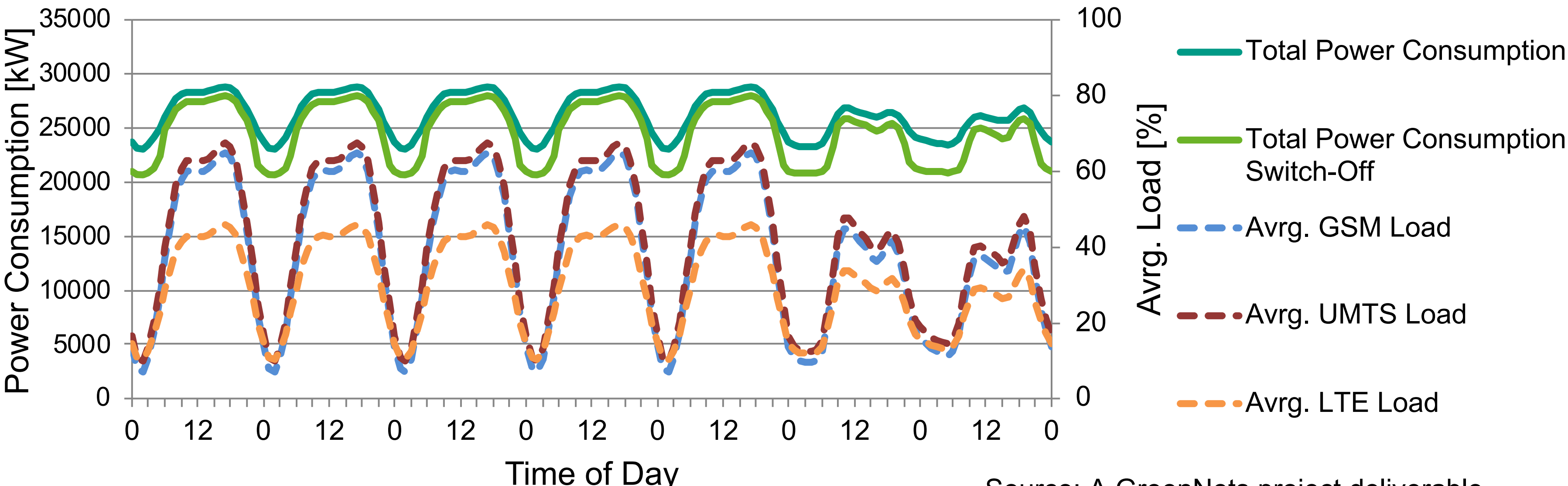
Energy-Saving Optimization

Traffic Forecast → Optimize the Network Configuration

Energy Modelling → Optimize the Network Configuration

Optimize the Network Configuration → Save Energy

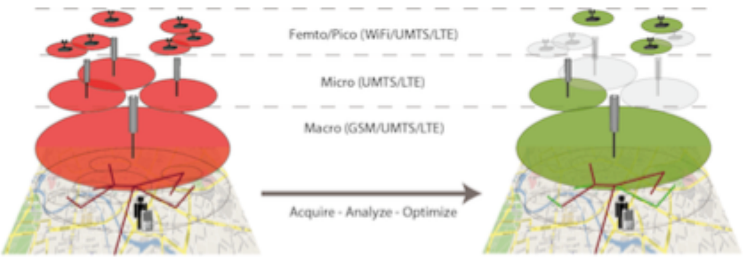
Source: A GreenNets project deliverable



Source: A GreenNets project deliverable

Energy-Saving Optimization

- Simulation area: 20 km x 20 km
- Number of iterations in our algorithm: 10
- Single-RAT optimization (LTE)
- Using CPLEX in the iteration of the algorithm
- Conventional laptop (Core i7 with 4GB of ram)



Source: www.communicate-green.de

# Cells	# test points	Considered cells per test point	# opt var	Time [s]	Memory usage [%]	#active cells after optimization
900	20.000	900	1.5 mio	276	70-80	440
900	20.000	10	0.19 mio	41	30-40	440
900	20.000	5	0.09 mio	29	30-40	516

Outlook

Reconstruction techniques based on tensors, which seem a natural fit for online tracking of channel conditions

Learning A2A radio maps

- D2D communication