TECHNISCHE UNIVERSITÄT WIEN

Bundesministerium Arbeit und Wirtschaft

Christian Doppler Forschungsgesellschaft

Real-World AI-Driven RAN Optimization using Digital Twins

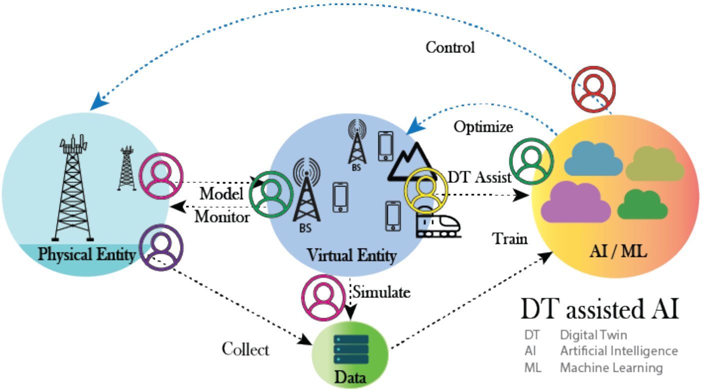
Wilfried Wiedner

CD-Lab for Digital Twin Assisted AI for Sustainable Radio Access Networks

BOWW 2025

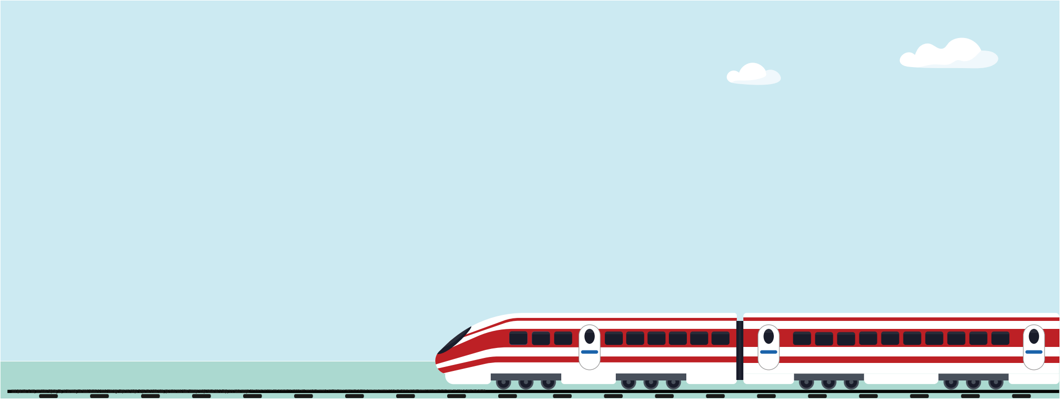
09.09.2025

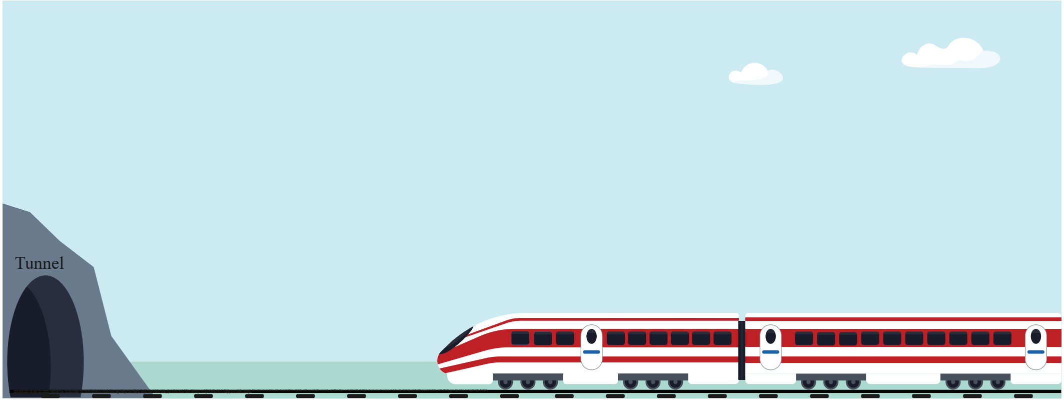
institute of telecommunications



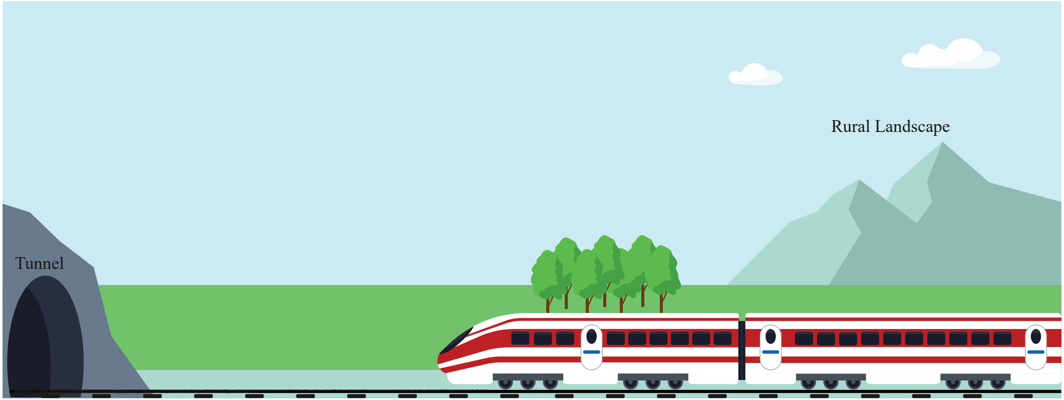
- Data-driven Digital Twin (DT) creation for centralized, local, and distributed AI
- Design and conduct large-scale measurement campaigns
- Distributed cooperative reinforcement learning for online resource optimization
- Preserve explainability across all DTs

Digital Twin for Railway Connectivity

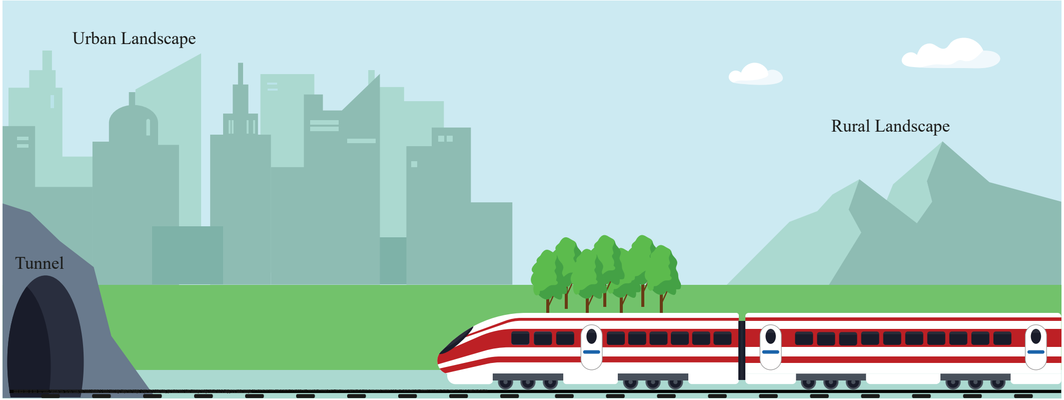



Tunnel

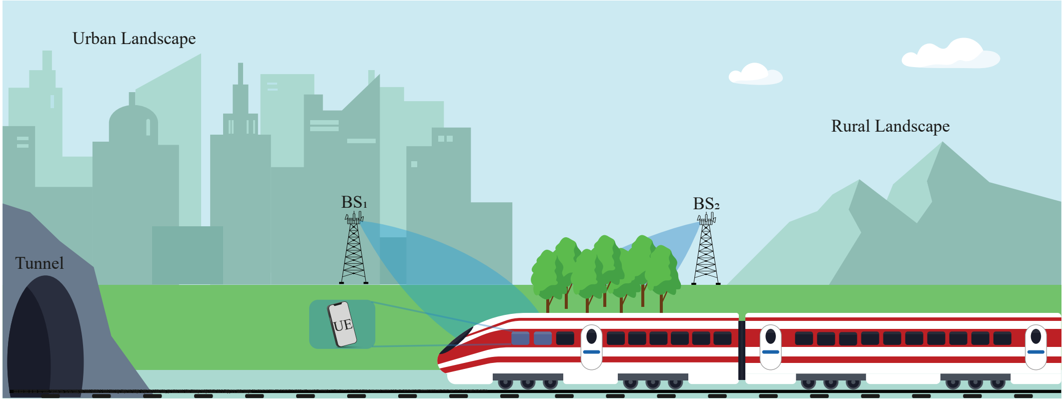
Digital Twin for Railway Connectivity



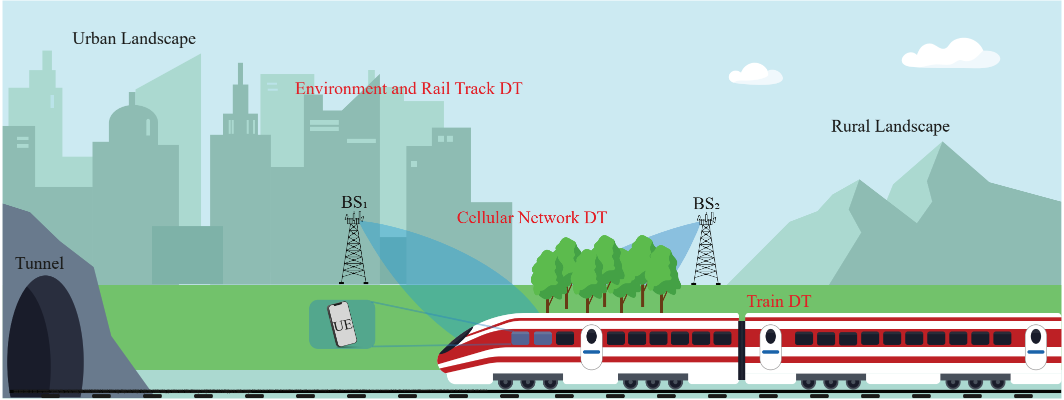
Digital Twin for Railway Connectivity



Digital Twin for Railway Connectivity

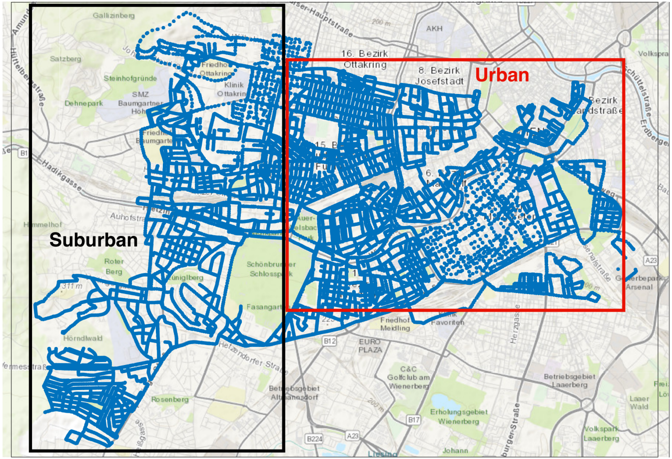


Digital Twin for Railway Connectivity



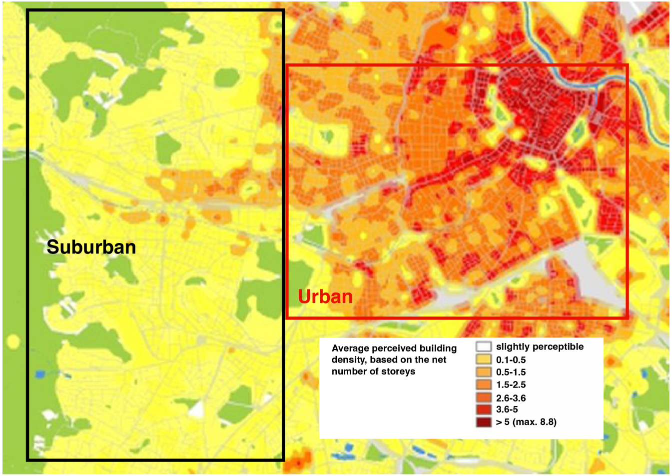
Digital Twin (DT) enables virtual modeling of railway systems and benchmarking different solutions.

- Passive scanner and phones
- approx. $100\,\mathrm{km}^2$
- approx. $30\mathrm{k}$ locations
- Urban and suburban
- LTE: $800\,\mathrm{MHz}$, $1.8\,\mathrm{GHz}$, $2.6\,\mathrm{GHz}$
- 5G: $2.1\,\mathrm{GHz}$, $3.5\,\mathrm{GHz}$



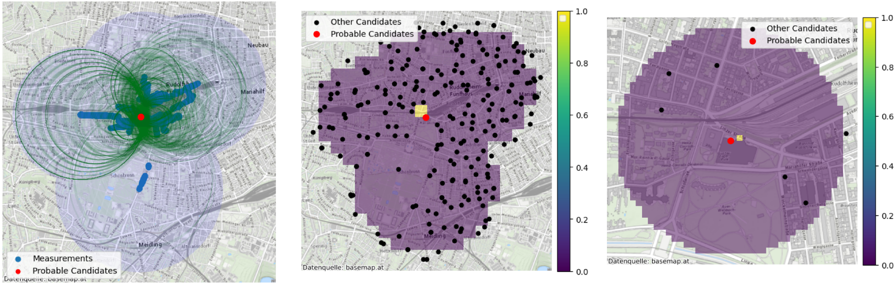
Measurement Campaign, Drive-test Dataset

- Passive scanner and phones
- approx. $100\,\mathrm{km}^2$
- approx. $30\mathrm{k}$ locations
- Urban and suburban
- LTE: $800\,\mathrm{MHz}$, $1.8\,\mathrm{GHz}$, $2.6\,\mathrm{GHz}$
- 5G: $2.1\,\mathrm{GHz}$, $3.5\,\mathrm{GHz}$



The Network Twin

- Timing advance (TA) based localization

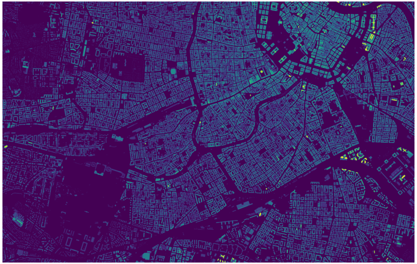


TA-based posterior localization. Left: TA coverage with probable candidates. Middle: coarse grid posterior. Right: zoomed-in estimate near MAP.

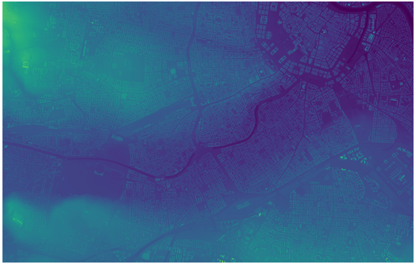
- Estimated sector orientations (Azimuth) - weighted centroids
- Estimated antenna heights

Vienna 3D City Model

- Publicly available, provided by Stadvermessung Wien
- We provide terrain and building data

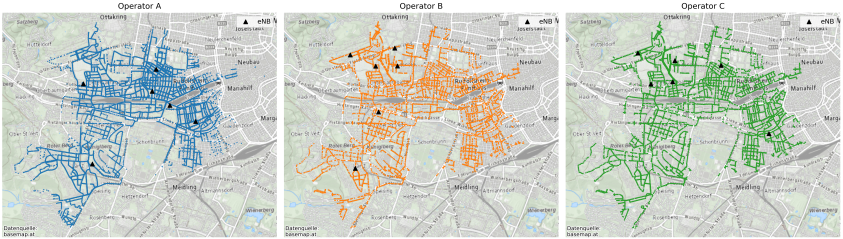


3D building model



3D city model (building and terrain combined)

Currently Available: LTE Subset

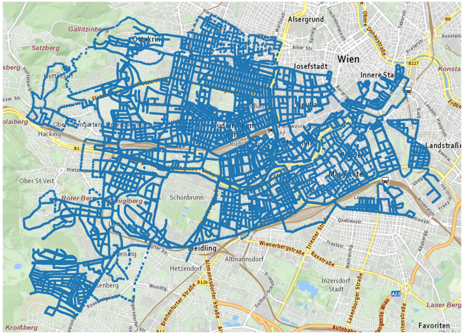


LTE Subset - click me

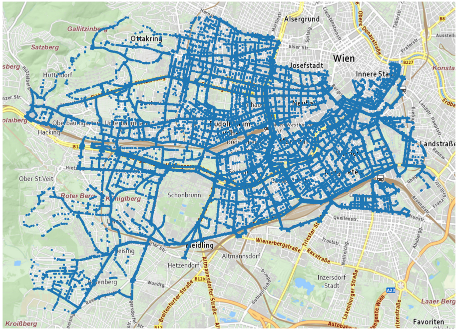
- LTE subset of three MNOs
- Subset covers urban and suburban region
- Network twins include estimated cell information of 6 most frequent base stations per MNO
- Building and terrain data is provided
- Python scripts:
  - TA-based base station localization
  - Deep learning network planner

Minimization of Drive Tests

- Network-side data source, network as seen from UEs
- Some of our use cases:
  - Coverage analysis in rural areas
  - Training of ML models
  - Traffic models
  - Cross-validation of different data sources



Scanner locations



MDT locations

- **Rasterized height profile with $1\ m$ resolution:**

  $F_{\text{buildings}}(\cdot)\ \ldots$ building height $\quad F_{\text{elevation}}(\cdot)\ \ldots$ elevation

  $$F_{\text{env}}(\cdot) = F_{\text{elevation}}(\cdot) + F_{\text{buildings}}(\cdot)$$

- **Propagation environment for measurement i:**

  $d_h\ \ldots$ horizontal distance to BS $\quad d_v\ \ldots$ vertical distance to BS

  $$l_{\text{geo}}^{(i)} = \begin{cases} 1, & f_{env}(d,0) < f_{dp}(d) \text{ for } d \in (0, d_{\text{h}}] \\ 0, & \text{else} \end{cases}$$

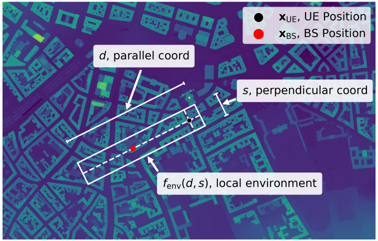
  $$f_{\text{dp}}(d) = d_v / d_{\text{h}} \cdot d + h_{\text{UE}} \quad \ldots \quad \text{profile of direct path}$$

- **Binary indicator for 3GPP Urban (UMa) model:**

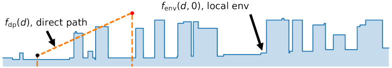
  $g_{\text{LOS}}\ \ldots$ LOS model $\quad g_{\text{NLOS}}\ \ldots$ NLOS model

  $$\hat{y}_{\text{dB}}^{(i)} = l_{\text{geo}}^{(i)} \cdot g_{\text{los}}\left(\mathbf{m}_{\text{uma}}^{(i)}\right) + \left(1 - l_{\text{geo}}^{(i)}\right) \cdot g_{\text{nlos}}\left(\mathbf{m}_{\text{uma}}^{(i)}\right)$$

  UMa Performance: **9.77 dB MAE**



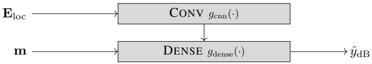
Local Env, $f_{\text{env}}^{(i)}(d, s)$



[1] L. Eller et al., "A Deep Learning Network Planner: Propagation Modeling Using Real-World Measurements and a 3D City Model", IEEE Access.

- **Metadata $\mathbf{m}$ and local environment $\mathbf{E}_{\text{loc}}$ as inputs:**

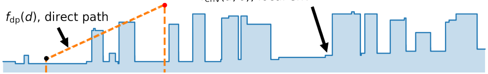
$$\hat{y}_{\text{dB}} = g_{\text{nn}}\left([\mathbf{E}_{\text{loc}}, \mathbf{m}]\,; \boldsymbol{\theta}_{\text{nn}}\right) \qquad \mathbf{m} = \left[d_h, d_v, f, \phi_h'', \phi_v'', \hat{y}_{\text{los}}, \hat{y}_{\text{nlos}}, l_{\text{geo}}\right]$$



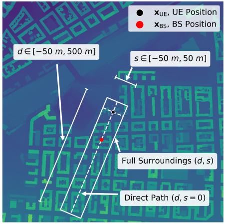
Include antenna parameters through UMa — separated from propagation.

- **Three variants for propagation environment $\mathbf{E}_{\text{loc}}$:**

ConvNet Full Surroundings (FS) . . . propagation environment in surroundings
ConvNet Direct Path (DP) . . . sequence input of profile along direct path
RefNet Metadata (MD) . . . UMa equivalent with only l_{geo} indicator



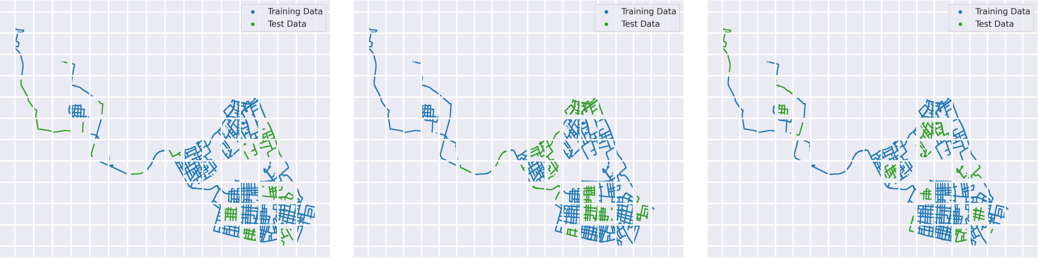
ConvNet DP



Propagation Environment

Ensuring Proper Generalization Analysis

- Network planning requires generalization $\rightarrow$ spatially separated $\mathcal{T}_{\text{train}}$ and $\mathcal{T}_{\text{test}}$ sets.
- Three-Fold cross validation with $500\ m$ spatial binning and $100\ m$ buffer distance.

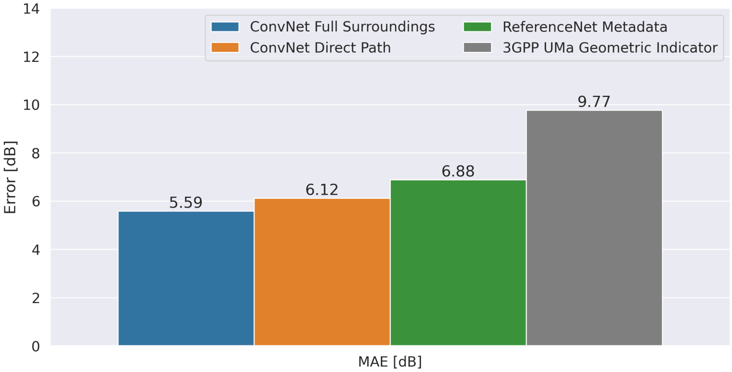


$\mathcal{T}_{\text{train}}^{(0)}$ and $\mathcal{T}_{\text{test}}^{(0)}$ $\quad$ $\mathcal{T}_{\text{train}}^{(1)}$ and $\mathcal{T}_{\text{test}}^{(1)}$ $\quad$ $\mathcal{T}_{\text{train}}^{(2)}$ and $\mathcal{T}_{\text{test}}^{(2)}$

Measurement position for $\mathcal{T}_{\text{train}}$ and $\mathcal{T}_{\text{test}}$ folds.

Real-World Performance Evaluation

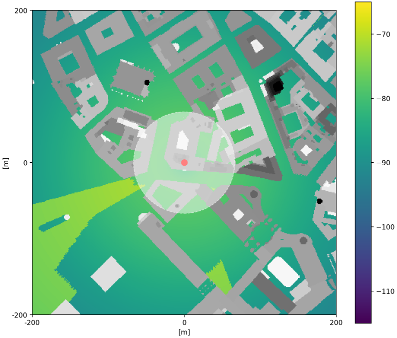
Results over all folds $\mathcal{T}_{\text{test}}^{(j)}$ with $j \in \{0, 1, 2\}$



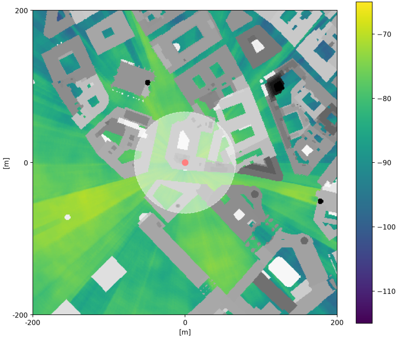
- UMa suffers from abstractions in form of binary indicator → high error in transition areas.
- Consistent error reduction by using environmental data with *ConvNet FS* performing best.

Comparing Learned Propagation Mechanisms

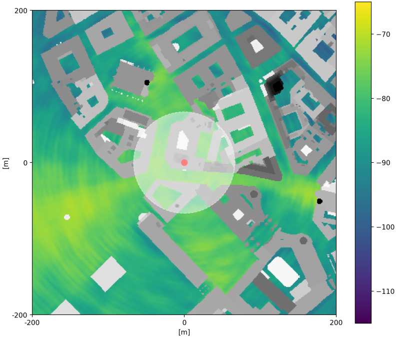
Scenario: $P_{\text{tx}} = 15$ dBm, $h_{\text{bs}} = 30\ m$, $f = 1800$ MHz, $\phi_{\text{sec,v}} = 0$, *Uniform Horizontal Pattern*



RefNet MD Prediction [dBm]

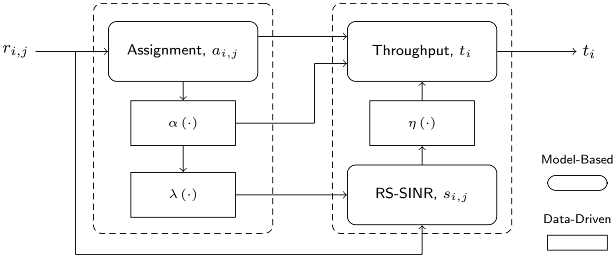


ConvNet DP Prediction [dBm]



ConvNet FS Prediction [dBm]

Differentiable Throughput Model



Soft Cell Assignment:

$a_{i,j} \in [0,1]$ ... assignment probability

u_j ... number of connected UEs

Traffic Patterns:

$\alpha(u_j)$ ... active UEs mapping

$\lambda(\alpha_j) \in [0,1]$ ... cell load mapping

Spectral Efficiency:

$s_{i,j}$ ... RS-SINR for each i, j combination

$\eta(s_{i,j})$ ... spectral efficiency mapping

Expression for Shared End-User Throughput:

$$t_i = B_{\mathrm{RB}} \cdot N_{\mathrm{RB}} \cdot \sum_{j=1}^{C} \frac{a_{i,j} \cdot \eta(s_{i,j})}{1 + \alpha(u_j)}$$

N_{RB} ... resource blocks $\qquad$ B_{RB} ... resource block bandwidth

L. Eller et al., "A Differentiable Throughput Model for Load-Aware Cellular Network Optimization Through Gradient Descent", IEEE Access.

Calibration to Traffic Patterns from Monitoring Data

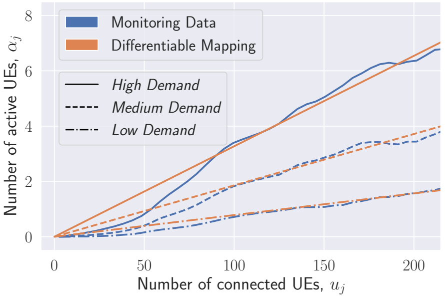


Figure: Active UEs Mapping: $\alpha(u_j)$

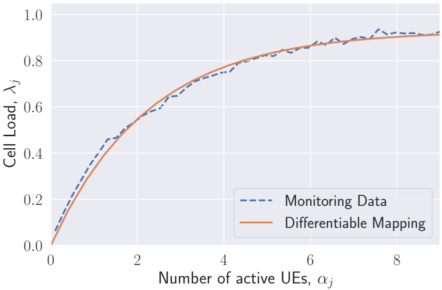
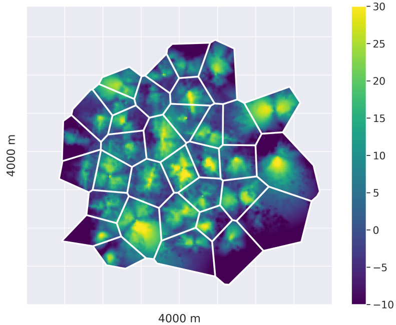


Figure: Cell-Load Mapping: $\lambda(\alpha_j)$

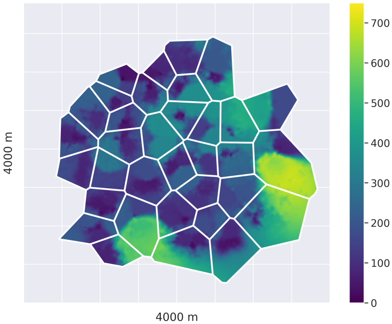
Describes average behavior in network, while ensuring the adequate level of abstraction

Load-Unaware Optimization

Real-world deployment with $C = 147$ cells. $t^{(\text{thresh})} = 10$ MBit/s, Transmit power: $p_j \in [-15, 15]$ dBm



Interference: RS-SINR, [dB]



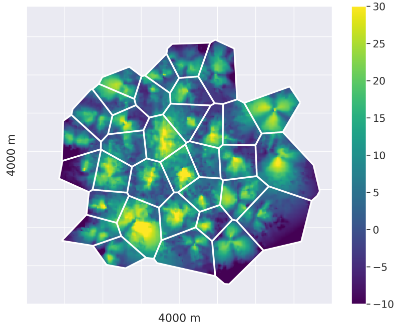
Congestion: UEs in same cell, [#]

Optimization Step = 0

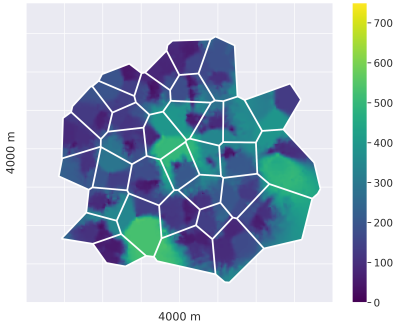
Outage Ratio: $\mathcal{L}_{\text{outage}} = 0.46$

Load-Unaware Optimization

Real-world deployment with $C = 147$ cells. $t^{(\text{thresh})} = 10$ MBit/s, Transmit power: $p_j \in [-15, 15]$ dBm



Interference: RS-SINR, [dB]

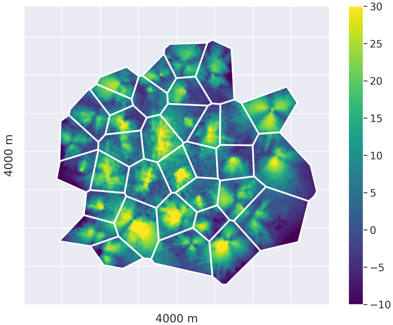


Congestion: UEs in same cell, [#]

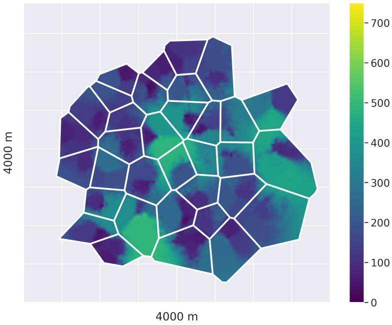
Optimization Step = 5

Outage Ratio: $\mathcal{L}_{\text{outage}} = 0.40$

Real-world deployment with $C = 147$ cells. $t^{(\text{thresh})} = 10$ MBit/s, Transmit power: $p_j \in [-15, 15]$ dBm



Interference: RS-SINR, [dB]

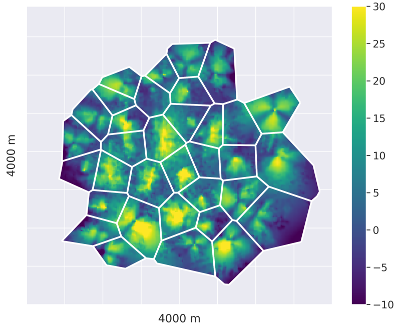


Congestion: UEs in same cell, [#]

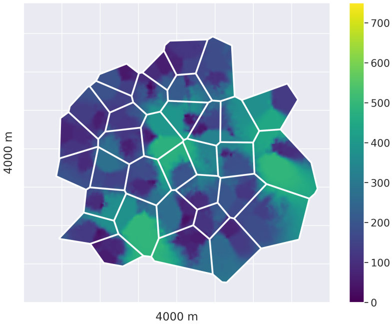
Optimization Step = 20

Outage Ratio: $\mathcal{L}_{\text{outage}} = 0.40$

Real-world deployment with $C = 147$ cells. $t^{(\mathrm{thresh})} = 10$ MBit/s, Transmit power: $p_j \in [-15, 15]$ dBm



Interference: RS-SINR, [dB]



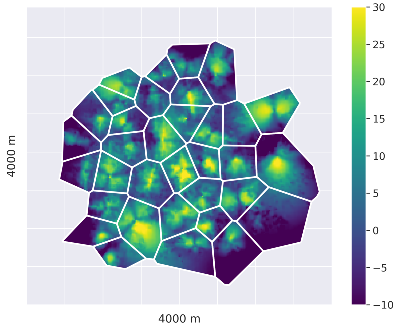
Congestion: UEs in same cell, [#]

Optimization Step = 50

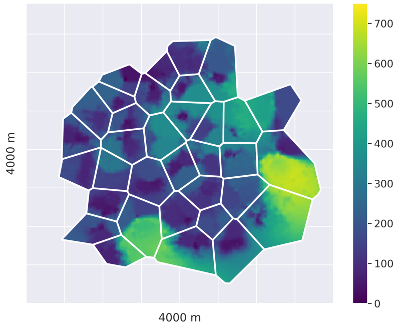
Outage Ratio: $\mathcal{L}_{\mathrm{outage}} = 0.41$

Gradient Descent-Based Transmit Power Optimization

Real-world deployment with $C = 147$ cells. $t^{(\text{thresh})} = 10$ MBit/s, Transmit power: $p_j \in [-15, 15]$ dBm



Interference: RS-SINR, [dB]



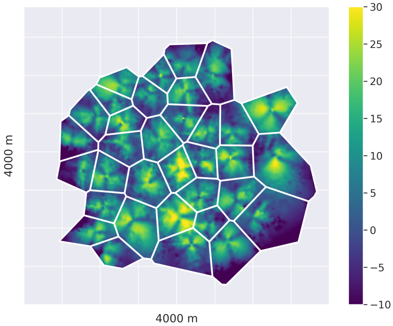
Congestion: UEs in same cell, [#]

Optimization Step $= 0$

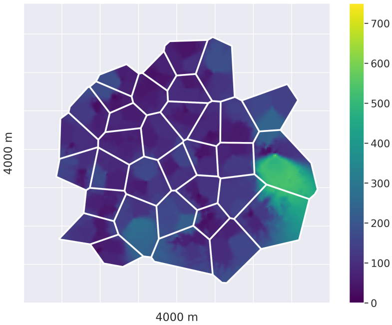
Outage Ratio: $\mathcal{L}_{\text{outage}} = 0.46$

Gradient Descent-Based Transmit Power Optimization

Real-world deployment with $C = 147$ cells. $t^{(\text{thresh})} = 10$ MBit/s, Transmit power: $p_j \in [-15, 15]$ dBm



Interference: RS-SINR, [dB]



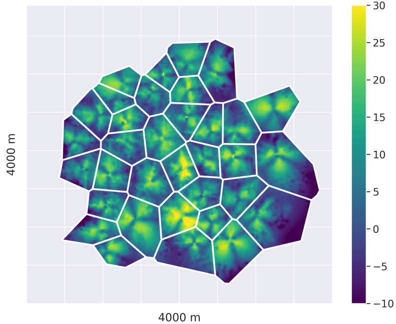
Congestion: UEs in same cell, [#]

Optimization Step = 5

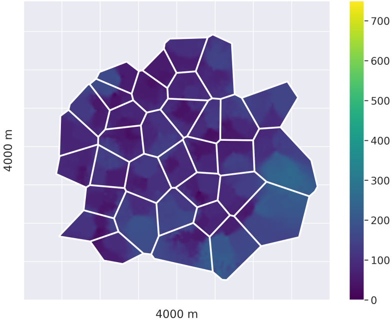
Outage Ratio: $\mathcal{L}_{\text{outage}} = 0.22$

Gradient Descent-Based Transmit Power Optimization

Real-world deployment with $C = 147$ cells. $t^{(\text{thresh})} = 10$ MBit/s, Transmit power: $p_j \in [-15, 15]$ dBm



Interference: RS-SINR, [dB]



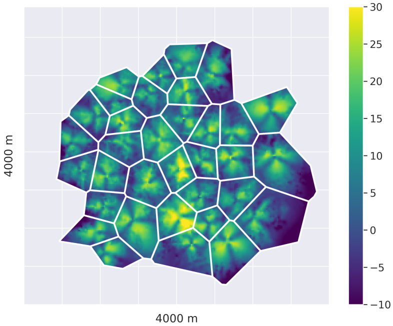
Congestion: UEs in same cell, [#]

Optimization Step = 20

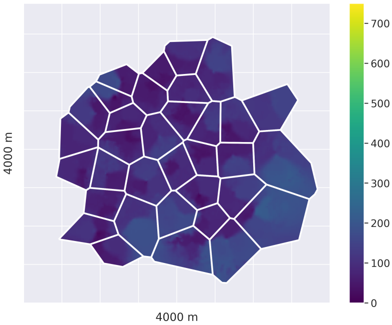
Outage Ratio: $\mathcal{L}_{\text{outage}} = 0.15$

Gradient Descent-Based Transmit Power Optimization

Real-world deployment with $C = 147$ cells. $t^{(\text{thresh})} = 10$ MBit/s, Transmit power: $p_j \in [-15, 15]$ dBm



Interference: RS-SINR, [dB]



Congestion: UEs in same cell, [#]

Optimization Step = 50

Outage Ratio: $\mathcal{L}_{\text{outage}} = 0.15$

Proposed objective adequately balances interference while avoiding overload cells

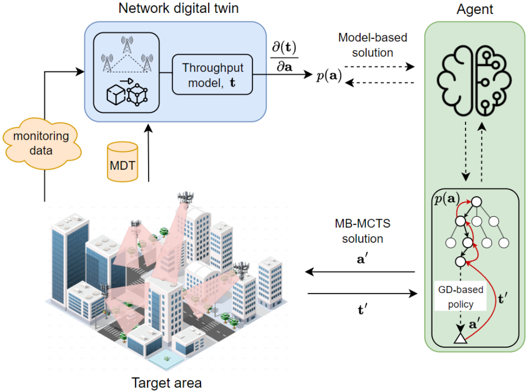
- **Tightly integrated hybrid optimization framework**[1]:
  - Monte Carlo Tree Search (MCTS) agent
  - Network twin providing domain knowledge
  - Interaction through reference solution

- **Problem Formulation & System Model:**

$$\text{Cells: } \mathcal{C} = \{1, 2, \ldots, C\}$$
$$\text{Actions: } \mathbf{a} = [a_1, a_2, \ldots, a_C]$$
$$\text{UEs: } \mathcal{U} = \{1, 2, \ldots, U\}$$
$$\text{Throughput: } \mathbf{t} = [t_1, t_2, \ldots, t_U]$$

$$\mathbf{a}^* = \arg\min_{\mathbf{a}} \ \mathbb{E}_{p(\mathbf{t};\mathbf{a})}\left[\mathcal{L}(\mathbf{t})\right]$$

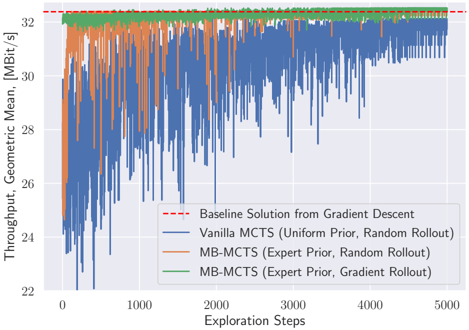
[1] L. Eller et al., "Safe Online Mobile Network Optimization through Digital Twin-Enhanced Monte Carlo Tree Search". In IEEE Transactions on Cognitive Communications and Networking, 2025.



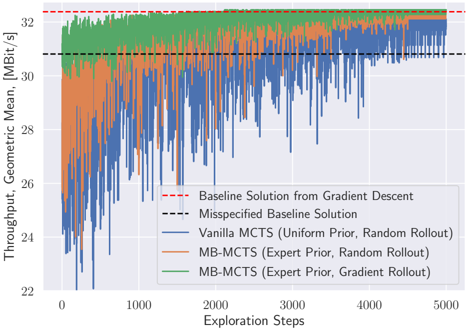
Proposed Optimization Framework

Safe Online Network Optimization

- Optimize downtilt for $C = 10$ cells
- Misspecified Twin: UE distribution, propagation conditions



Optimization history perfectly specified twin



Optimization history mismatched twin

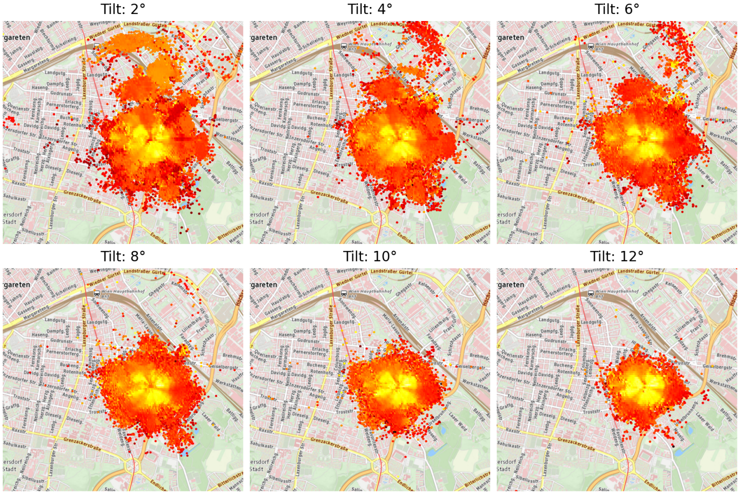
MDT-Based Evaluation of Antenna Tilt Changes

- Goal: AI/ML controls physical entity
- Real-time data from the physical into the virtual entity required
- Parameter changes reflected by MDT?

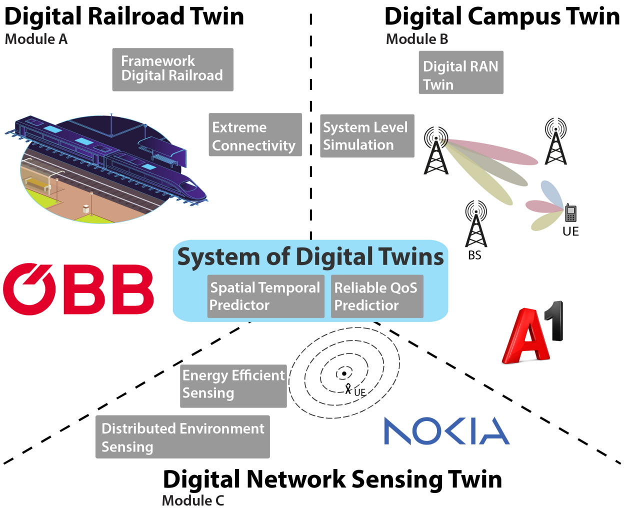
MDT-Based Evaluation of Antenna Tilt Changes

- Goal: AI/ML controls physical entity
- Real-time data from the physical into the virtual entity required
- Parameter changes reflected by MDT?
- Experiment:
  - Electrical downtilt changed periodically over three months
  - LTE 1800, two channels

MDT-Based Evaluation of Antenna Tilt Changes



Median serving cell RSRP



Staff	active
PostDoc	1
PhD cand.	3
MA	9
BA	1

Three upcoming PhD candidate positions

Information and Contact

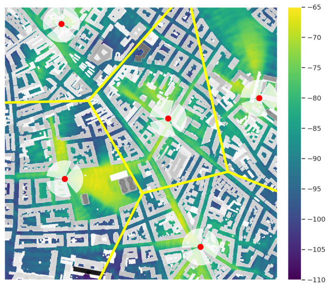
Models/Sourcecode

TECHNISCHE UNIVERSITÄT WIEN

Bundesministerium Arbeit und Wirtschaft

Christian Doppler Forschungsgesellschaft

Native AI Network Planning



Thank you for your attention!
Questions?

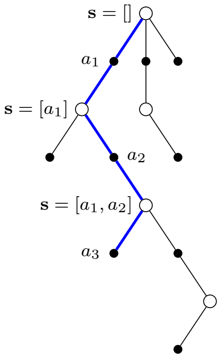
Wilfried Wiedner
wilfried.wiedner@tuwien.ac.at

institute of telecommunications

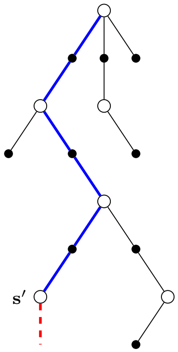
Extra

Monte Carlo Tree Search for Network Optimization

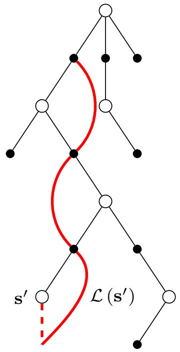
Turn optimization into a search tree $\mathbf{a} = [a_1, a_2, \ldots, a_C]$ Specifying the configuration for cell $c \in \mathcal{C}$



1. Selection Policy



2. Rollout Policy

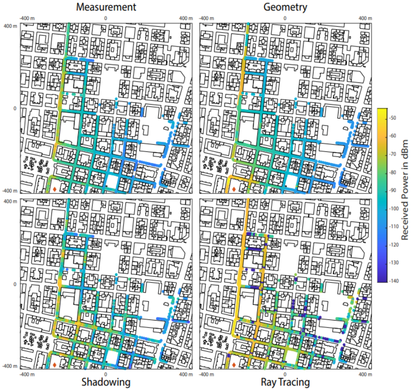


3. Backup Step

Design expert selection and rollout policies using the digital twin $\rightarrow$ safe and accelerated exploration

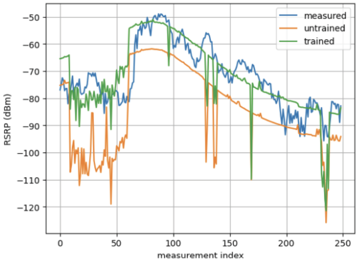
Simulations vs Real world measurements

- RSRP - Reference Signal Received Power (LTE)
- Comparison of pathloss models with RSRP measurement
- Empirical validation of ray tracing for predicting signal strength in cellular networks



A. **Fastenbauer** et al., "Comparison of Large-Scale Fading Models with RSRP Measurements" (Jun. 2024)
S. Schwarzmann, "Empirical validation of ray tracing for predicting signal strength in cellular networks" (Jun. 2024)
S. Dolezel, "Time Series Forecasting and Clustering Techniques for Cellular Network Performance for Predictive Load Management" (Sep. 2024)
K. Chmela, "Validation of Ray-Tracing Systems for Mobile Communication: Simulations and Field Measurements in one Vienna District" (Sep. 2024)

- Digital Twin
  - 3D city model (City of vienna),
  - Material database (Raytracer),
  - Network layout (Sendekataster),
  - Clutter data (CloudRF, ESA).
- Drive test railroads in Vienna
- Simulation raytracing tool



K. Guan et al., "Key technologies for wireless network digital twin towards smart railways" High-speed Railway (2024)