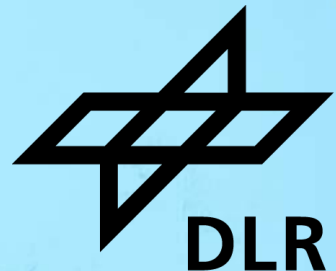




HOW SYSTEM CONFIGURATION SHAPES DEMAND

Agent Based Simulation of Mobility-on-Demand systems & policy insights



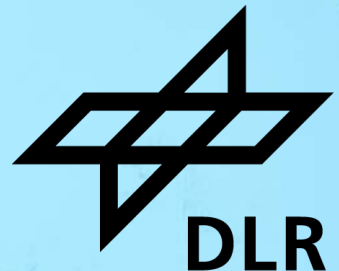
Agenda

1. Context and research objectives
2. Using agent-based transport simulation as a decision support tool
3. The relationship between MoD system configuration and ridership
4. Rebalancing as a tool to decrease heterogeneity of wait times
5. Summary and Conclusion



HOW SYSTEM CONFIGURATION SHAPES DEMAND

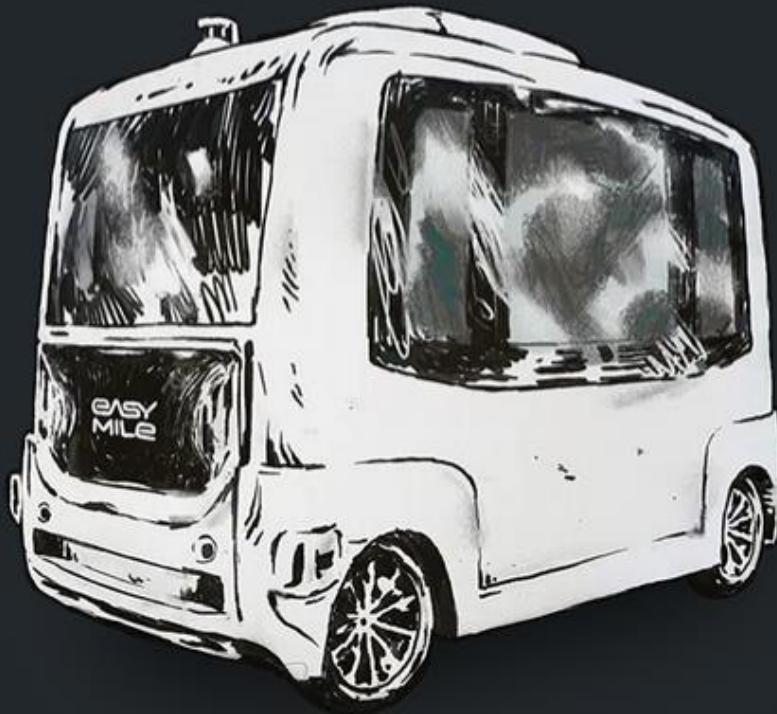
Context and research objectives



Project Context

KelRide: Weather-Proof Smart Shuttle

KelRide in a nutshell.



- Funding ~11 mill. €
- Total budget ~15.6 mill. €
- Project duration: 2021 - 2023
- The aim of the project was to **integrate an autonomous on-demand ridepooling (MoD) service** which can be operated in all weather conditions **into an already existing human-driven MoD service**
- www.kelride.com

Funded by:



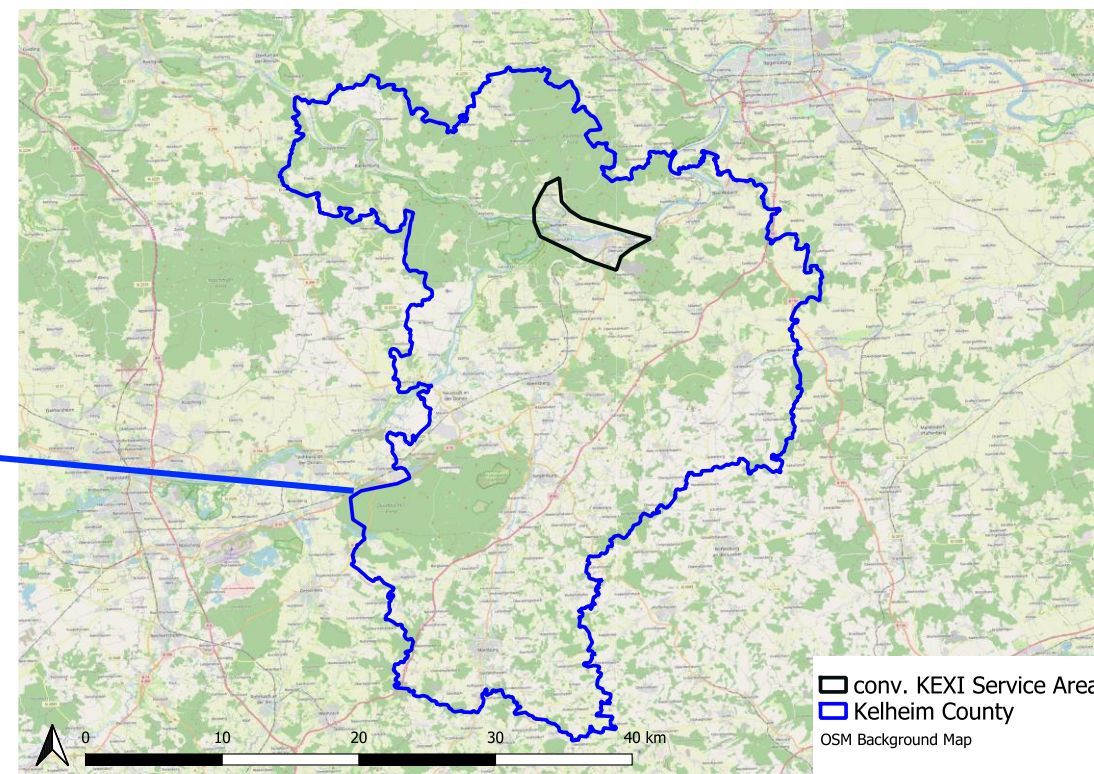
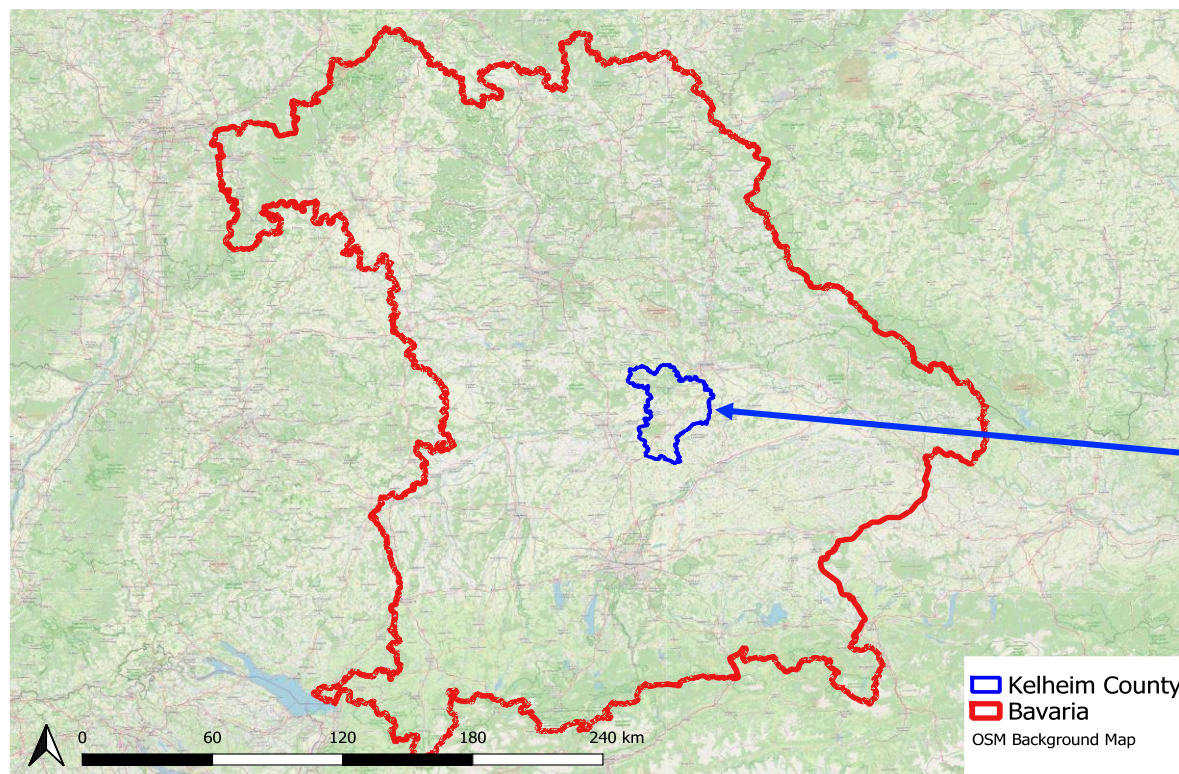
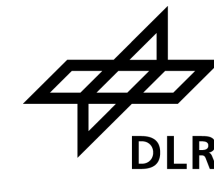
Federal Ministry
for Digital
and Transport





Spatial Context

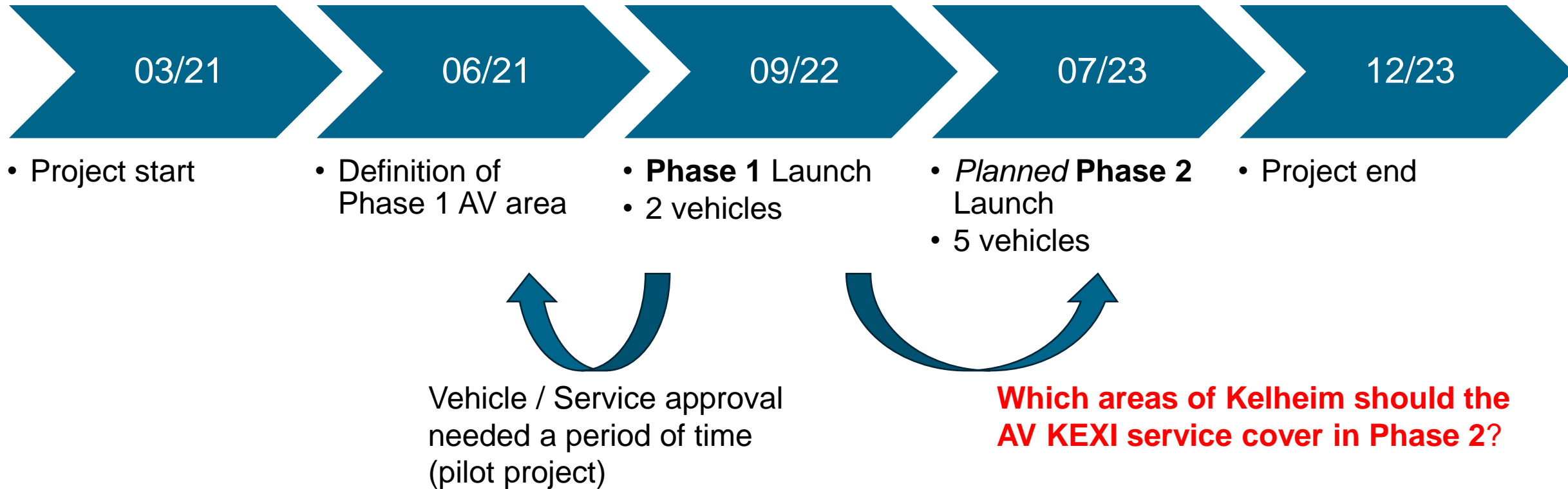
Kelheim County and Kelheim Town (Municipality)



Based on sources:[2], www.openstreetmap.org

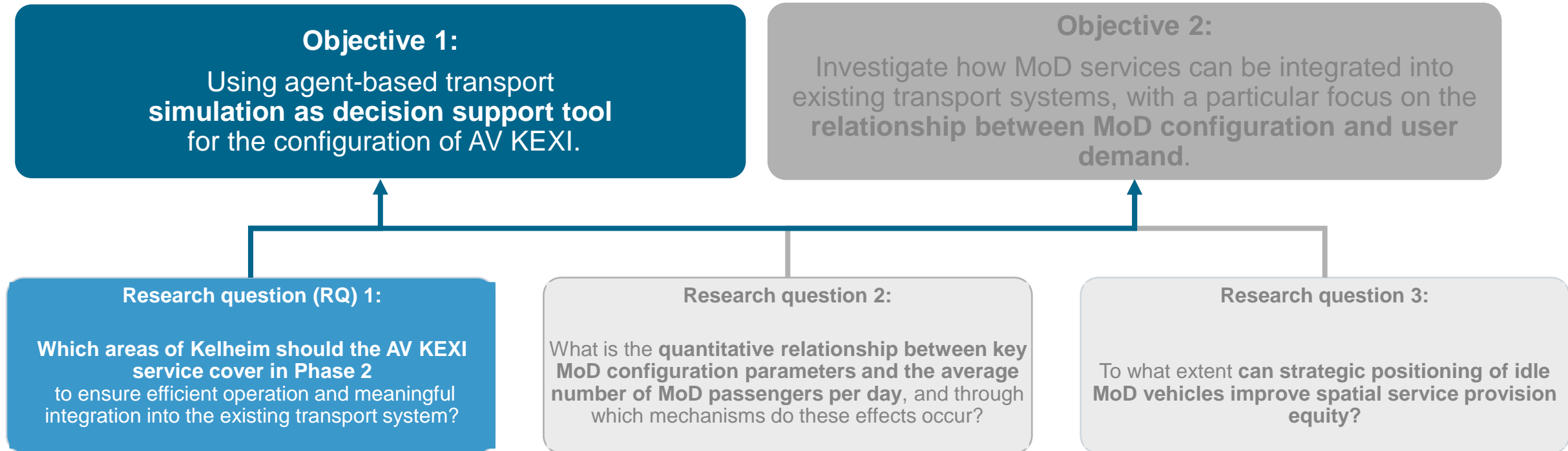
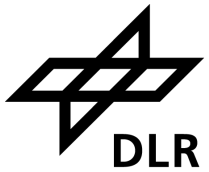


Planned Project Timeline: 2 Phases = 2 Fleet Sizes





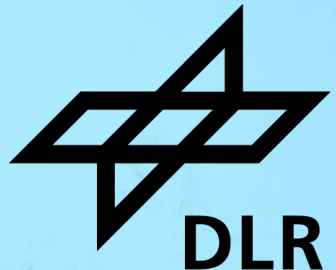
Research Objectives and Questions



USING AGENT-BASED TRANSPORT SIMULATION AS A DECISION SUPPORT TOOL

Which areas of Kelheim should the AV KEXI service cover in Phase 2?

The content of this section based on [2]. Corresponding copyrights and licenses apply.



Simulation Framework

MATSim – Multi-Agent Transport Simulation

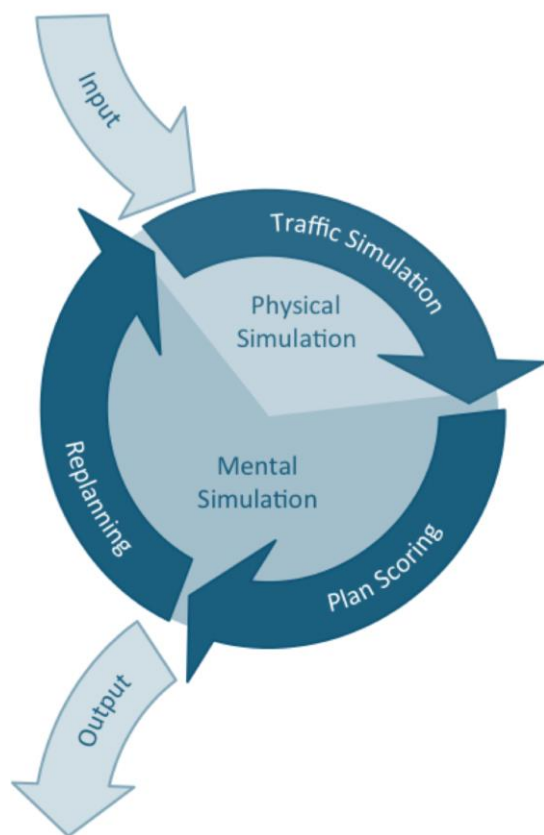
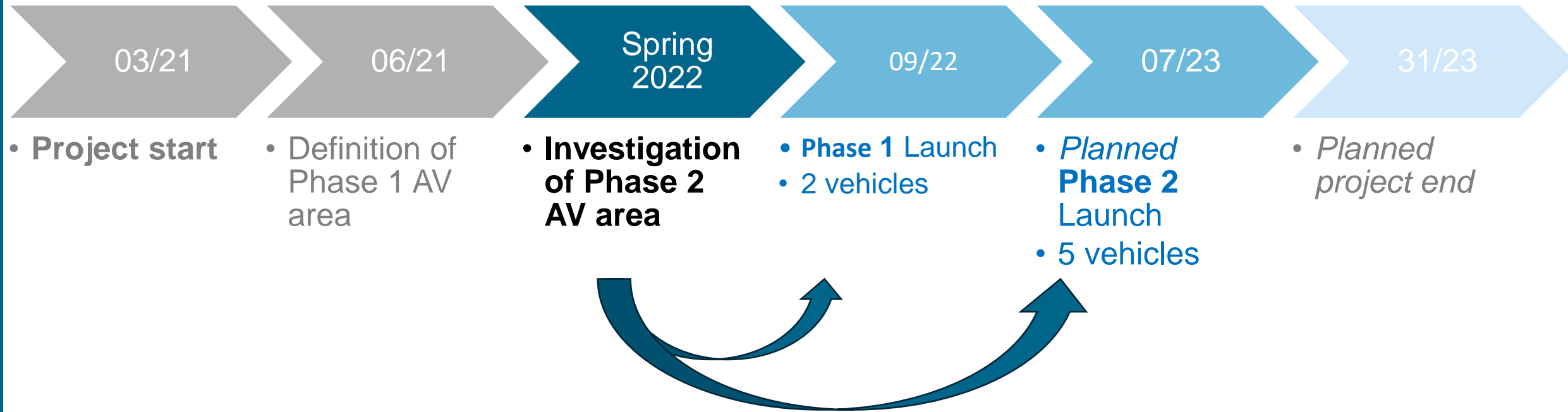


Image based on sources: [3,9]

- Agent-, activity- and event-based, dynamic transport simulation framework [4]
- Modular, various extensions, widely used and adopted
- **Physical simulation**
 - Queue model
- **Mental simulation**
 - Behavioral adoption through **co-evolutionary learning algorithm**
 - Mode choice, Route choice, Departure time choice, ...
- Approximates stochastic user equilibrium
- **Allows to investigate interaction of transport demand and supply**



Project and Study Timeline



Study 1 = Projection of

- Phase 1 (already configured)
- Phase 2 -> decision support

→ no real AV booking data available

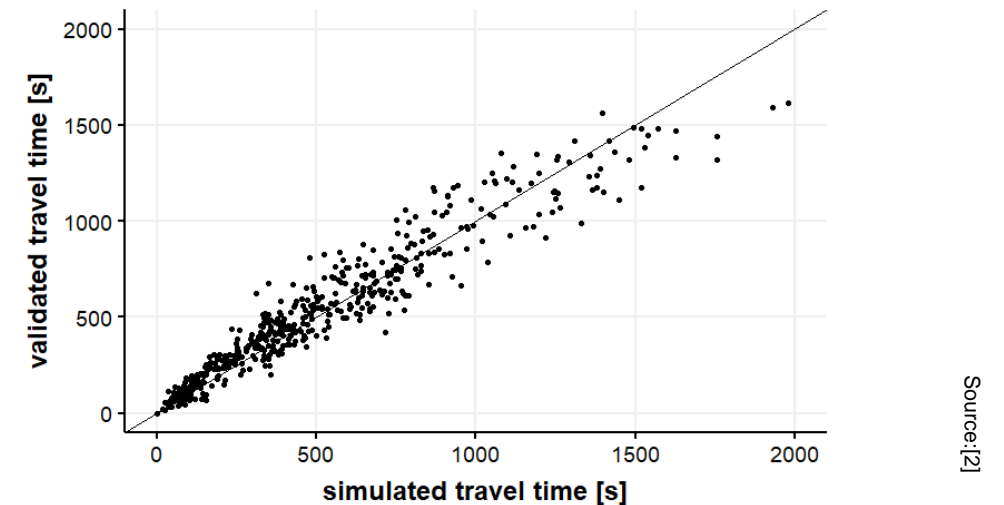
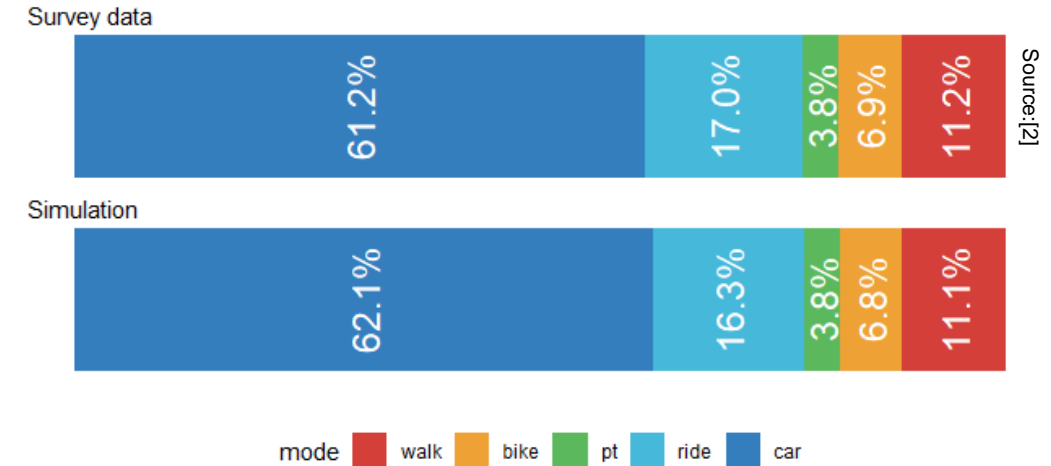
Base Model Calibration + Validation

Synthetic transport demand

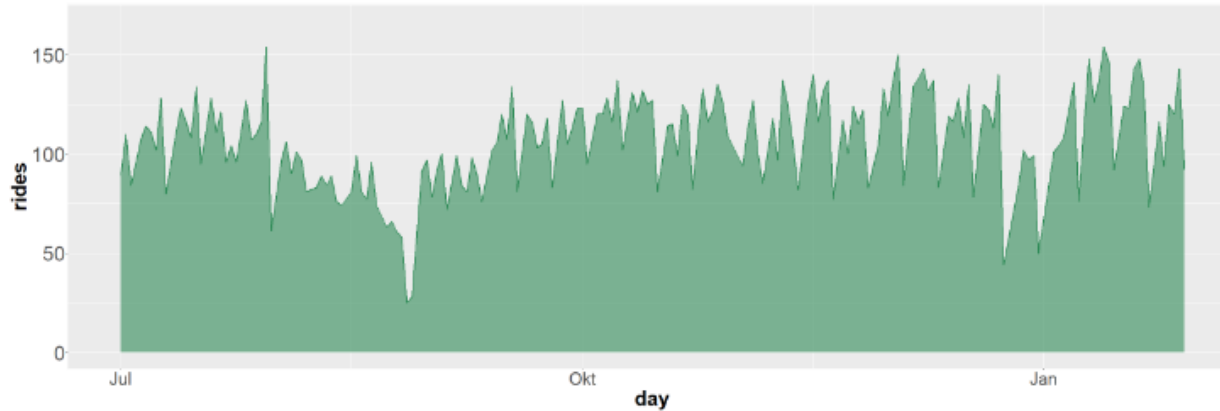
- Trajectories derived from mobile phone data
- Regional statistics
- Travel surveys
- ...

Calibration & Validation

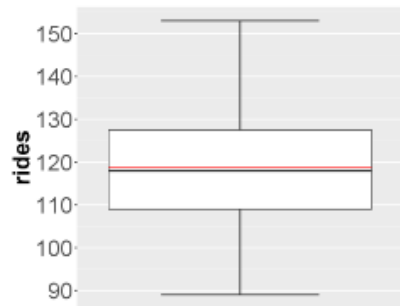
- Modal split
- Modal distance distribution
- Travel times
- Traffic counts



Mobility-on-Demand (MoD) Real-Data-Driven Calibration



(a) demand over time

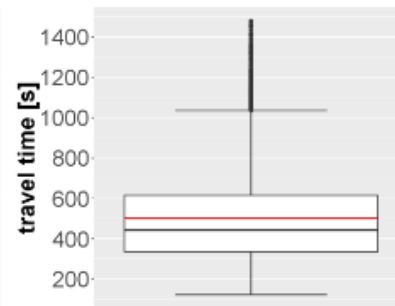


(b) rides per day

Source:[2]



(c) travel distances (stop to stop)



(d) travel times

- Statistics of real data on the **conventional KEXI service** for the time span **July 2021 until January 2022**.
- Each simulation case is run with 5 different random seeds (during calibration and for policy cases)

Runs	Nr. of rides	Mean Euclidean trip distance [m]	Mean travel time [s]
Run 1	121	2453	489
Run 2	120	2184	453
Run 3	127	2317	453
Run 4	124	2331	487
Run 5	108	2402	454
Average	120	2338	467
Target	119	2100	503

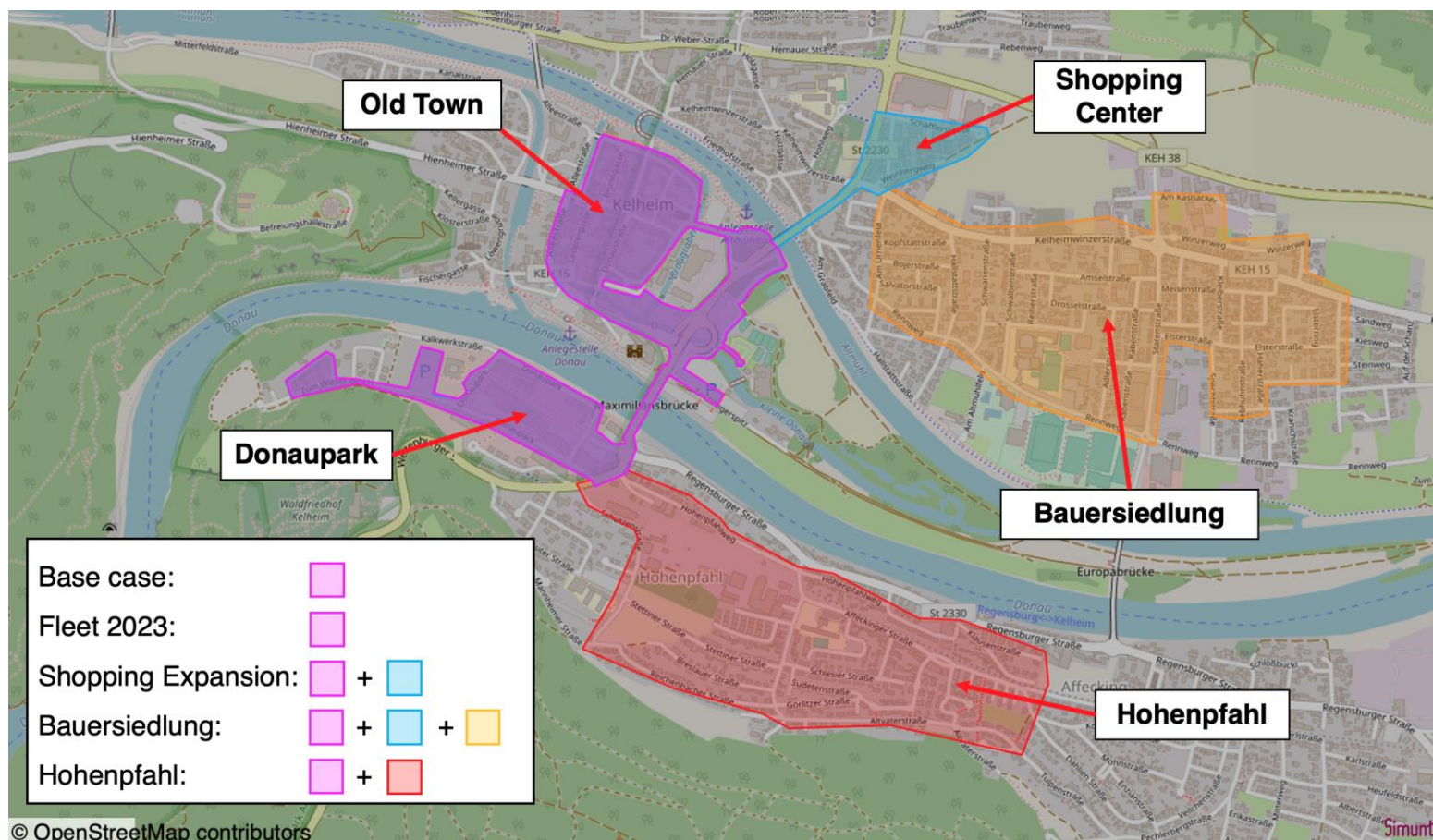
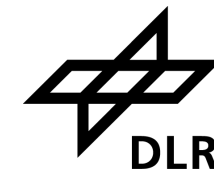
Source:[2]

The red lines in the box plots display the mean value, while black lines inside the boxes display the median.



Policy Cases

AV Fleet Expansion + Service Area Expansion

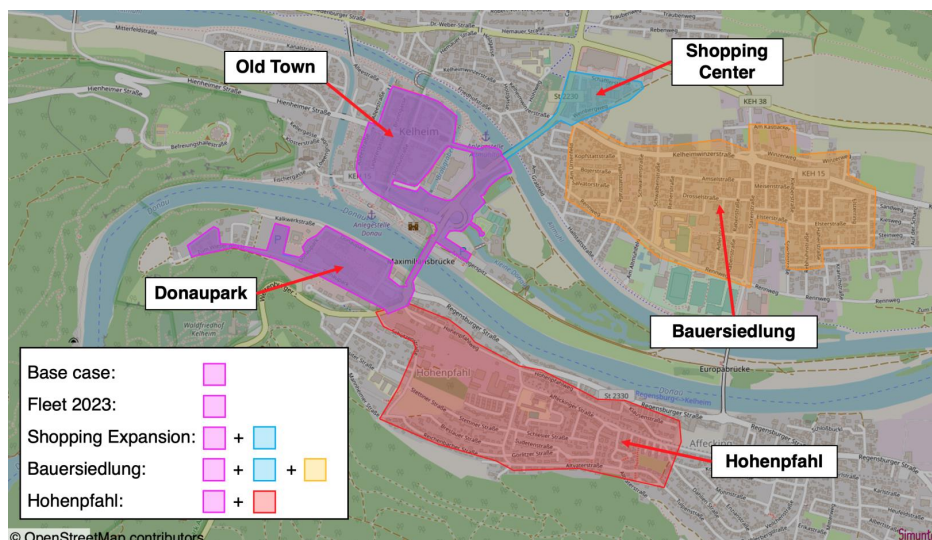


Source:[2]

Case study	Nr. of AV
Base Case	2
Fleet 2023	5
Shopping Expansion	5
Bauersiedlung	5
Hohenpfahl	5

Results

Demand Statistics

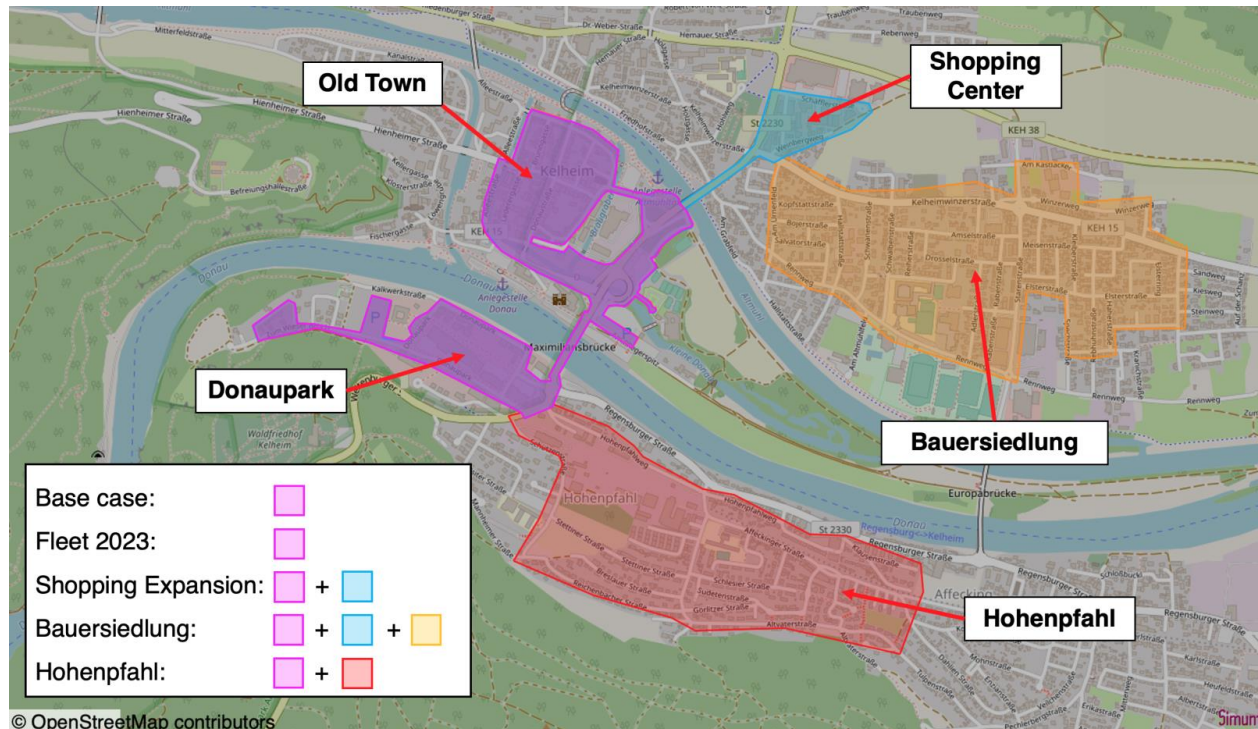


Source:[2]

Case	Number of rides per day / per veh-h	Mean waiting time [s]	Mean trip Euclidean distance [m]	Mean travel time [s]	Mean Euclidean speed [m/s]
Autonomous KEXI					
Base	41 / 2.9	199	634	268	2.37
Fleet 2023	51 / 1.5	180	620	272	2.28
Shopping Expansion	65 / 1.8	247	838	395	2.12
Bauersiedlung	103 / 2.9	428	1205	579	2.08
Hohenpfahl	104 / 3.0	397	1154	573	2.01
Conventional KEXI					
Base	120 / 2.5	397	2394	470	5.09
Fleet 2023	119 / 2.5	388	2385	451	5.29
Shopping Expansion	126 / 2.6	398	2355	455	5.18
Bauersiedlung	123 / 2.6	383	2370	452	5.24
Hohenpfahl	125 / 2.6	380	2398	450	5.33



Key Findings Regarding RQ 1 and Project Decision



© OpenStreetMap contributors

Source:[2]

Key Findings:

Simulation results suggest that

- AV fleet expansion should be accompanied by area expansion (RQ1)
- AV fleet and conventional fleet are not competing
- AV ridership is attracted from eco-friendly modes

Project Decision

- expand the service area to Shopping Center + Bauersiedlung



THE RELATIONSHIP BETWEEN MOD SYSTEM CONFIGURATION AND RIDERSHIP

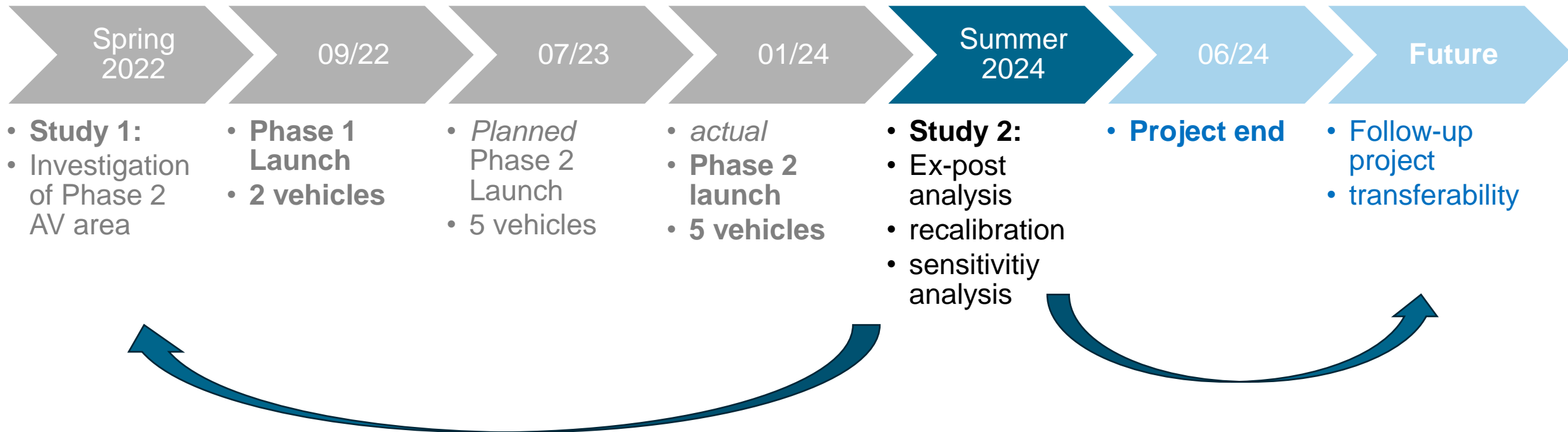
**Ex-post evaluation of the simulation projections +
Application of the lessons learned**

The content of this section based on [10]. Corresponding copyrights and licenses apply.





Project and Study Timeline

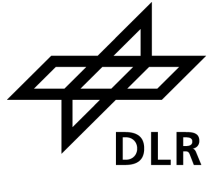


Study 2 = Evaluation of Study 1 + Projection of possible future scenarios (sensitivity study)

→ real AV booking data from Phase 1 and Phase 2 available



Evaluation of Study 1 and Recalibration based on Phase 2



- **Instead of ~40 rides per day** projected for Phase 1, **~0 rides per day were observed**

- Field tests and surveys revealed **reasons for discrepancy:**

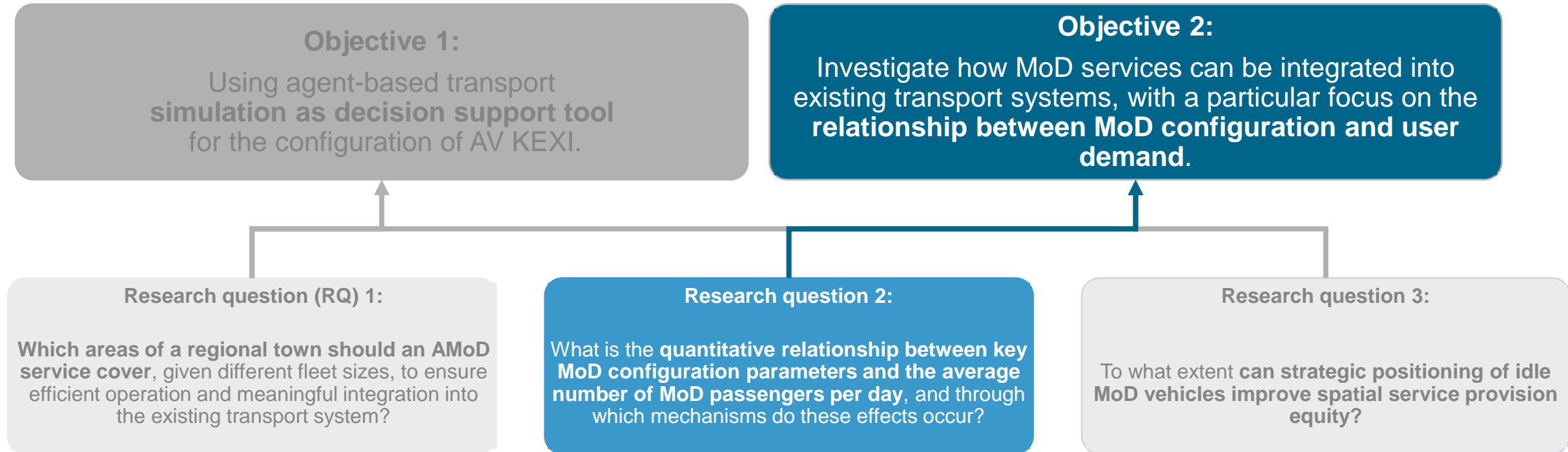
- Average speed ~9 km/h instead of ~18 km/h
- Limited vehicle availability (mostly 1 instead of 2)
- Difficulties in the booking process
- Negative attitude towards AV

Phase 2 yielded

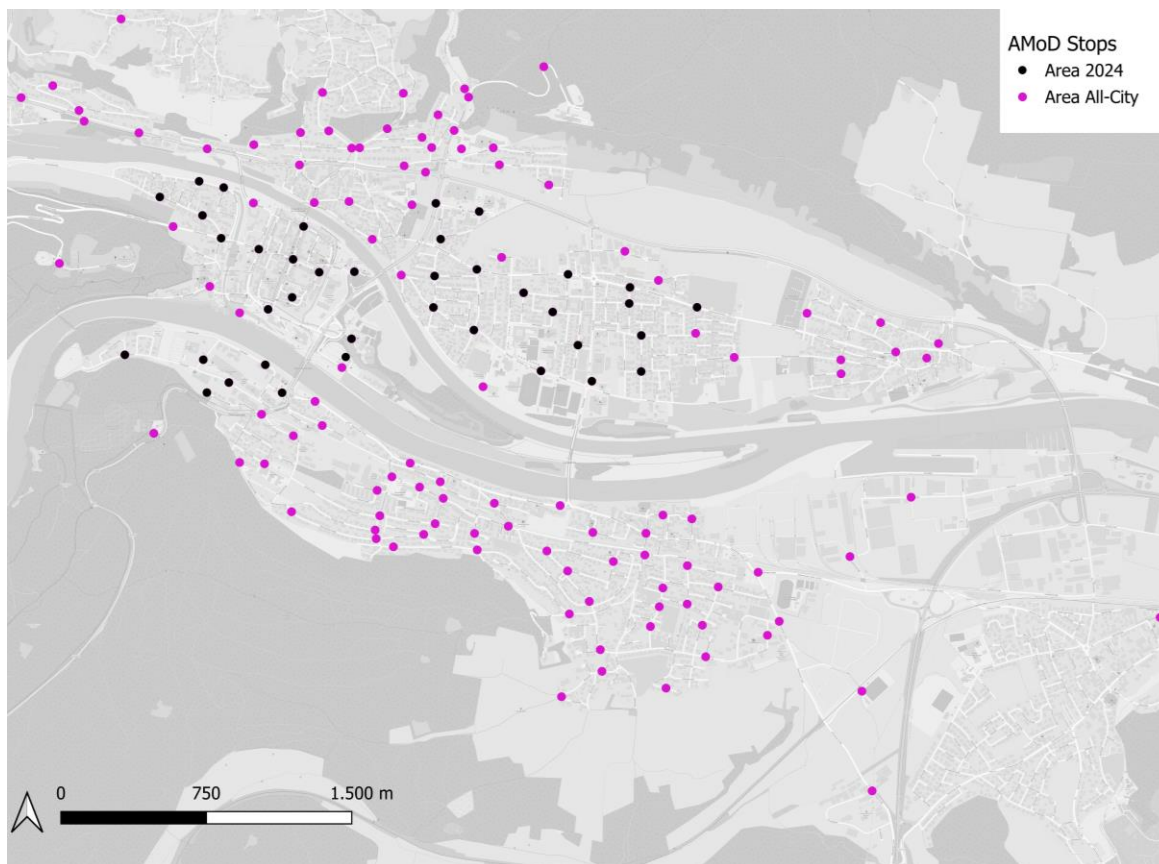
- Speed / Connectivity improvements
- Larger service area
- Larger fleet / higher vehicle availability
- Improvements in booking process

→ ~ 4.5 passengers per day

Research Objectives and Questions

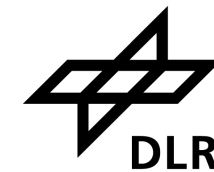


Sensitivity analysis variables

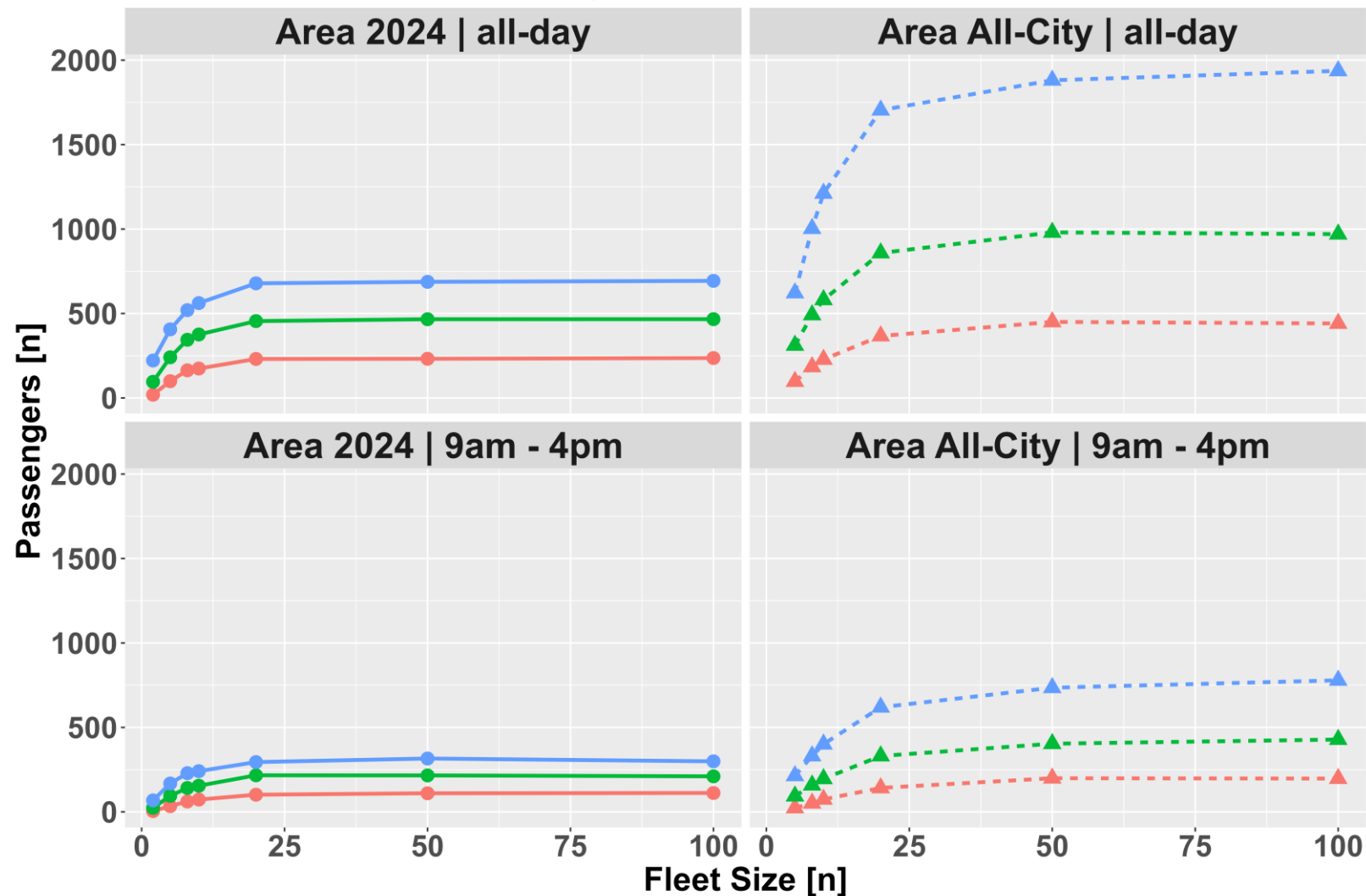


Based on sources:[10], www.openstreetmap.org

Configuration Parameter	Values
Area	Area 2024, All-City
Service times	9am-4pm, all-day
Fleet size	2, 5, 8, 10, 25, 50, 100
AV speed	12km/h, 18km/h, 30km/h



Nr. of AMoD passengers



Area



Operating times



Fleet size



Speed



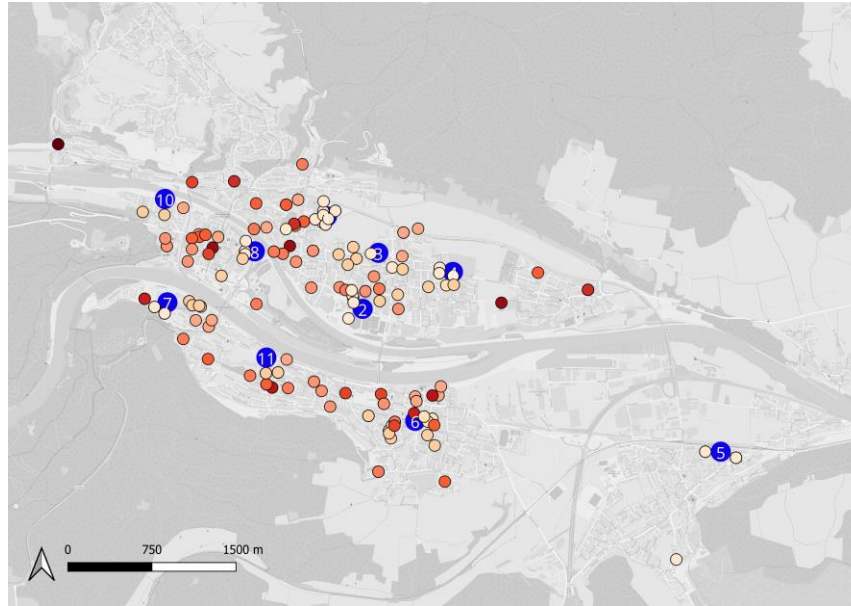
Speed ● 12 km/h ● 18 km/h ● 30 km/h

Service Area ● Area 2024 ● Area All-City

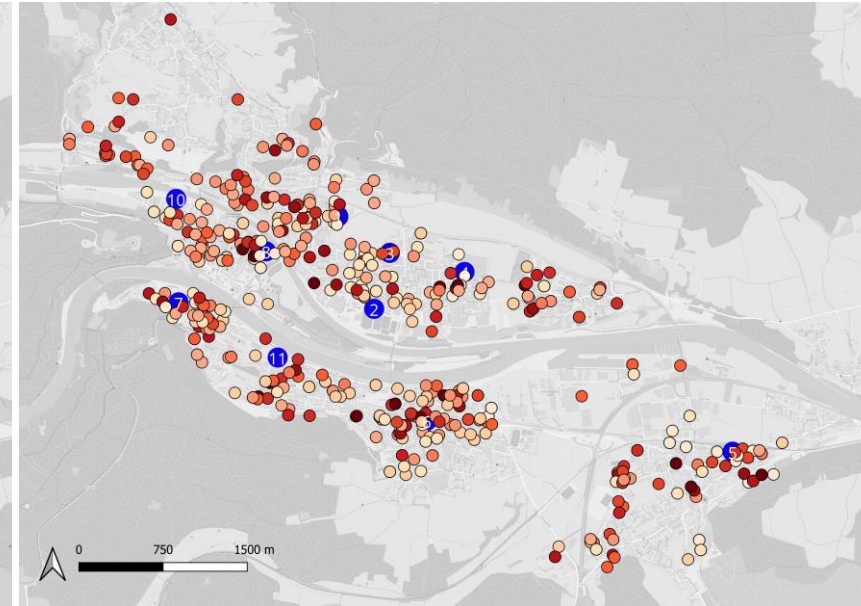
Source:[10]

Spatial Distribution of Wait Times

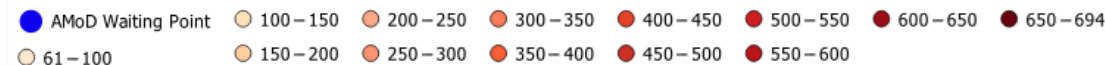
10 AV - 12 km/h



10 AV - 30 km/h



AMoD trip origins by wait time [s]



Based on sources:[10], www.openstreetmap.org

- The number of idling locations was limited, both in real-world and simulation
→ Implication on the relation of wait time and fleet size
- Results suggest **heterogeneity in wait times**, with higher probability for good service for trips originating near to an idling location (AMoD waiting point)

Results

Log-log Elasticities from Simulation

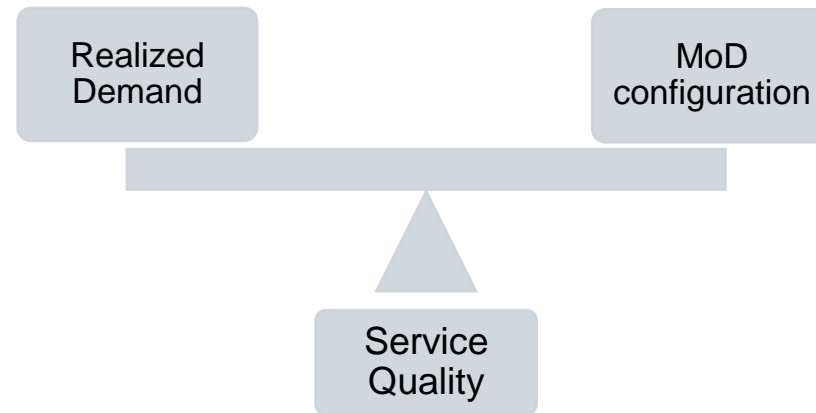
$$pSpeed_{avg} = \frac{totalRideDistance_{avg}}{totalTravelTime_{avg}} ; \log(passengers) \sim \log(pSpeed_{avg}) + \log(fleetSize)$$

Area	Service Times	Elasticity w.r.t. Speed β_{pSpeed}	$\beta_{fleetSize}$	Adjusted R ²
Area 2024	All-day	2.49 ***	0.27 ***	0.811
	9 am – 4 pm	2.57 ***	0.40 ***	0.744
Area All-City	All-day	2.94 ***	0.31 ***	0.924
	9 am – 4 pm	3.03 ***	0.45 ***	0.892

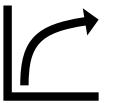
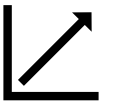
Total travel time elasticities obtained from discrete choice models estimated using stated preference data range between -0.5 and -1.5

Stars indicate the significance level: ***p < 0.001, **p < 0.01, *p < 0.05

Key Findings regarding RQ 2

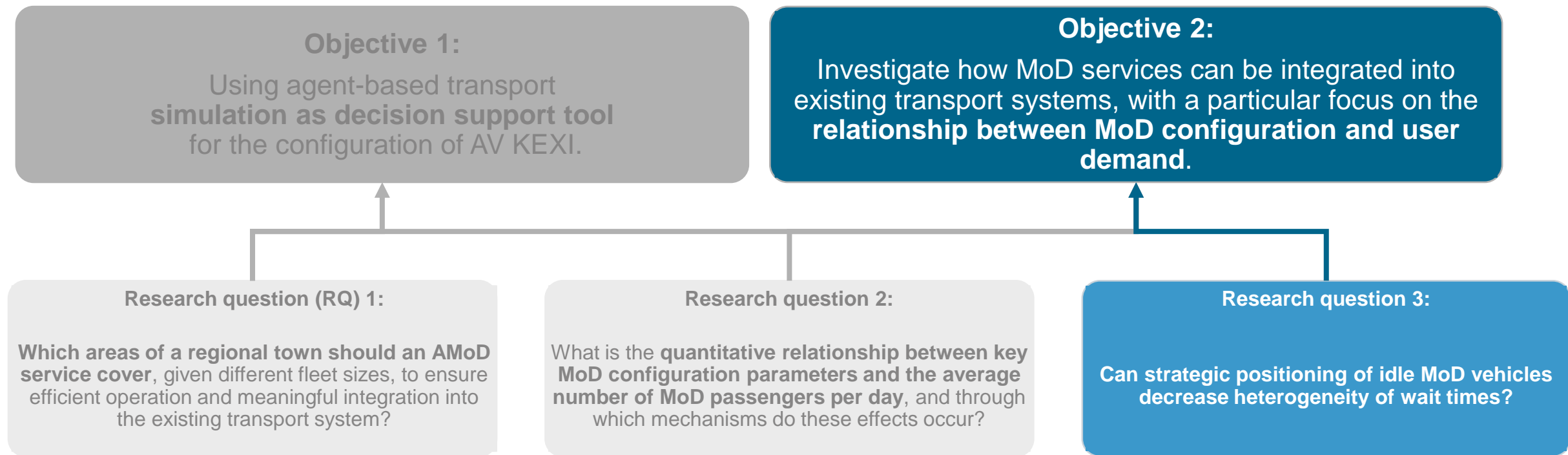


- Configuration **parameters influencing the demand *potential* of MoD** (service area, operating times) are found to have **linear relations** to the *realized* number of MoD passengers
- Configuration **parameters influencing the MoD service quality** (fleet size, vehicle speed) are found to have **superlinear impacts** on the *realized* number of MoD passengers
- High dependency of the results on the locations where vehicles idle and the distribution logic (rebalancing)





Research Objectives and Questions

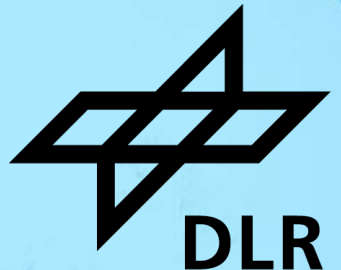




REBALANCING AS A TOOL TO DECREASE HETEROGENEITY OF WAIT TIMES

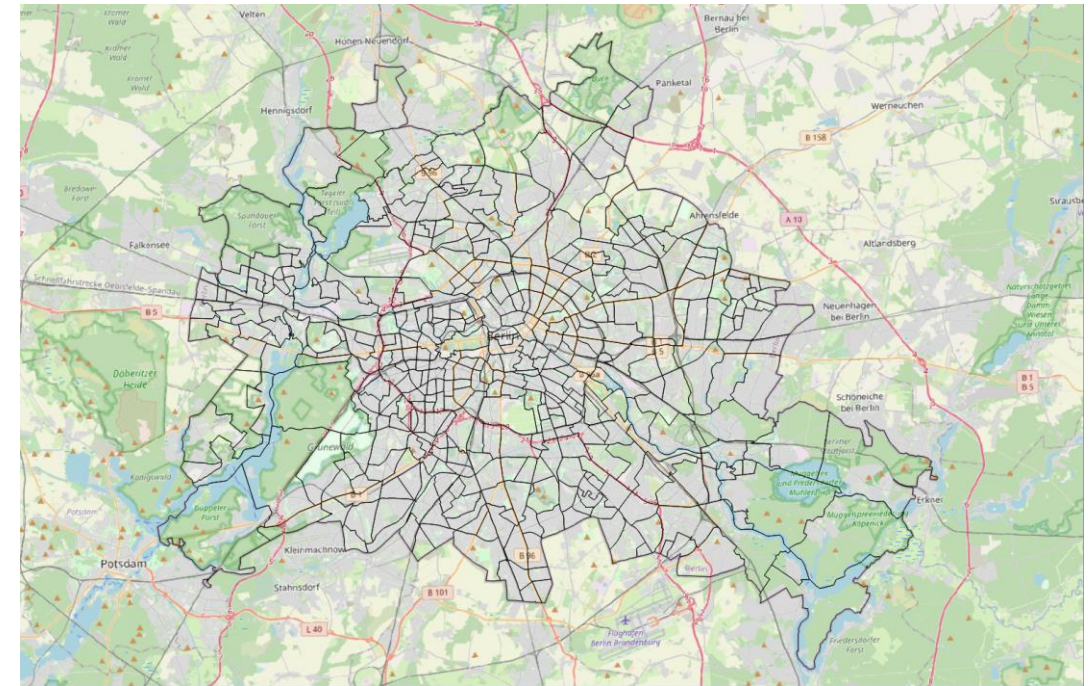
Application to the use case of Berlin

The content of this section based on [11]. Corresponding copyrights and licenses apply.



Motivation and Context

- A profit-oriented operator would concentrate vehicles in the city center [8], leading to unequal access (**heterogeneous wait times**) to the service
- Existing strategies for empty vehicle relocation (rebalancing) focus on demand throughput (ridership) and system efficiency
- Objective: provide equal wait times throughout the service area, while maintaining high ridership and efficiency
- Study area: Berlin



Based on sources:[11], www.openstreetmap.org

Rebalancing as Optimization Problem

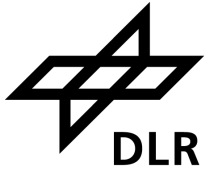
- Rebalancing as transportation problem [6]:
Find the minimum-cost vehicle flows from zones with a vehicle surplus to those with a vehicle deficit.
- Solved at a fixed time interval [5]
- Target function for the desired number of vehicles for zone i at time j : $t_{i,j} = a * e_{i,j} + b$
- Typically, $e_{i,j}$ is associated with the expected demand (ED), leading to inequality of zones
- New target formulations are investigated

Investigated Target Functions

1. No rebalancing (**base**)
 2. Estimated demand (**ED-R**) – exactly as in [6]
 3. Estimated demand (**ED**) - adjusted parameters
 4. Fixed number of vehicles per zone (**FNV**):
 5. Equal vehicle density (**EVD**)
 6. Equal vehicle-to-population ratio (**EVP**)
- Note that 4. – 6. are not time-dependent



Performance Indicators



1. (Spatial) Heterogeneity of wait times:

Standard deviation and spatial distribution of mean waiting time per zone s_w

2. Overall service level:

Mean T_W^{mean} and 95th percentile T_W^{p95} of *all* wait times

3. Ridership / Realized Demand:

Total number of rides and spatial distribution of trip starts

4. Operative efficiency:

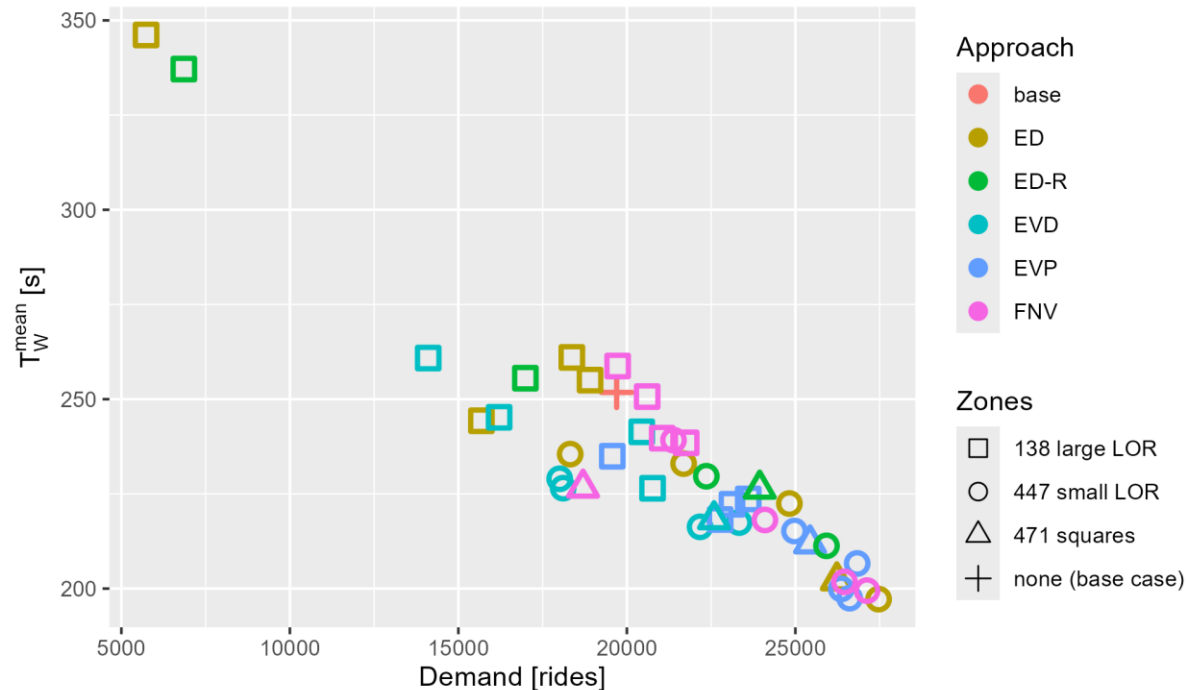
Ratio of empty vehicle kilometres travelled



Wait time and Realized Demand

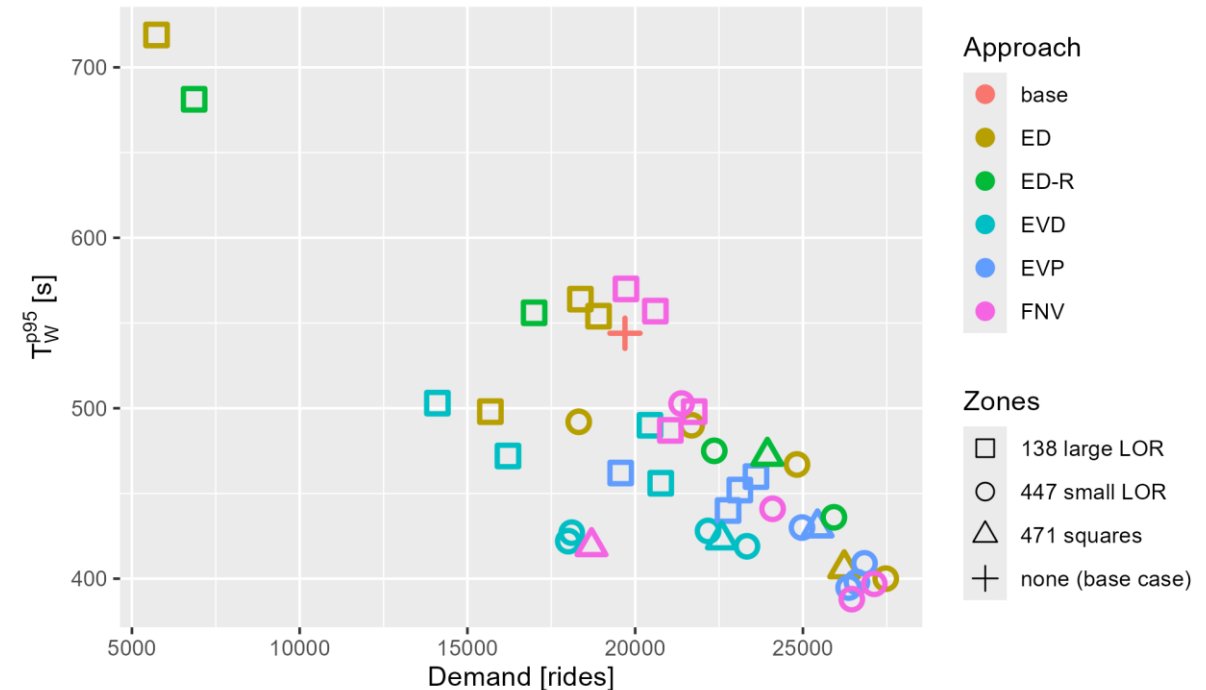
- Results suggest *linear* correlation between realized demand, mean and 95th percentile of waiting time
- Rebalancing systems with smaller zones lead to ~30% more rides and ~15% lower avg. wait time

Average wait time T_W^{mean} over demand



Source:[11]

95th percentile of wait times T_W^{p95} over demand



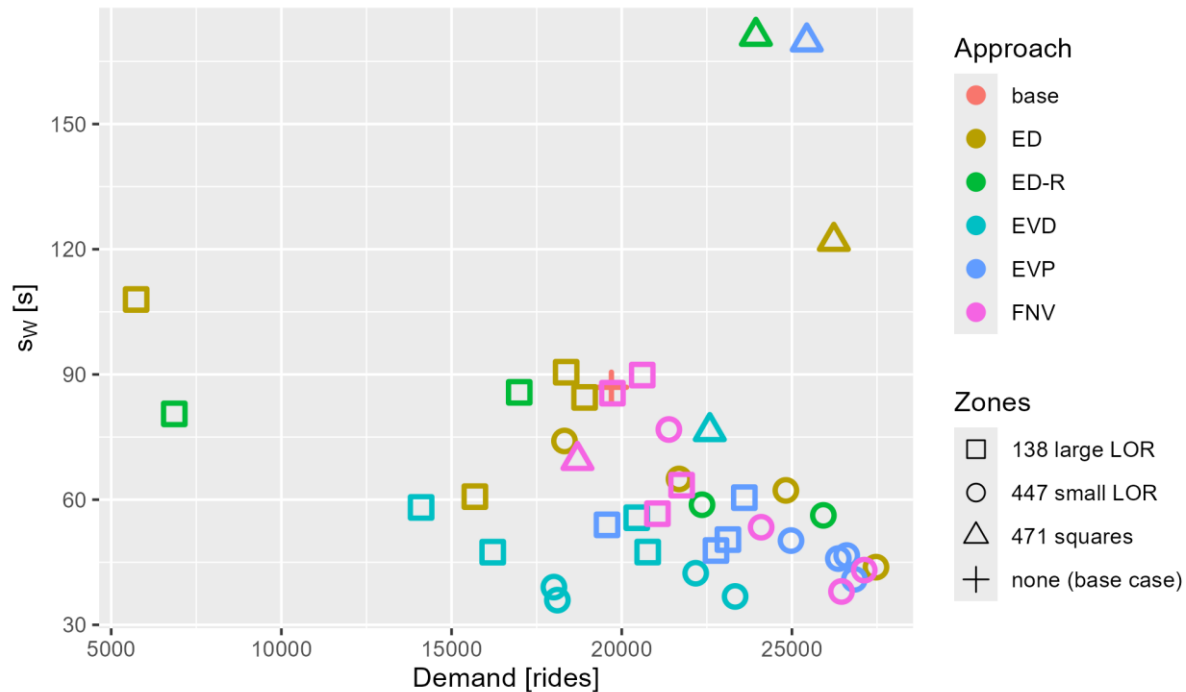
Source:[11]

Standard Deviation of Zonal Mean Wait Time



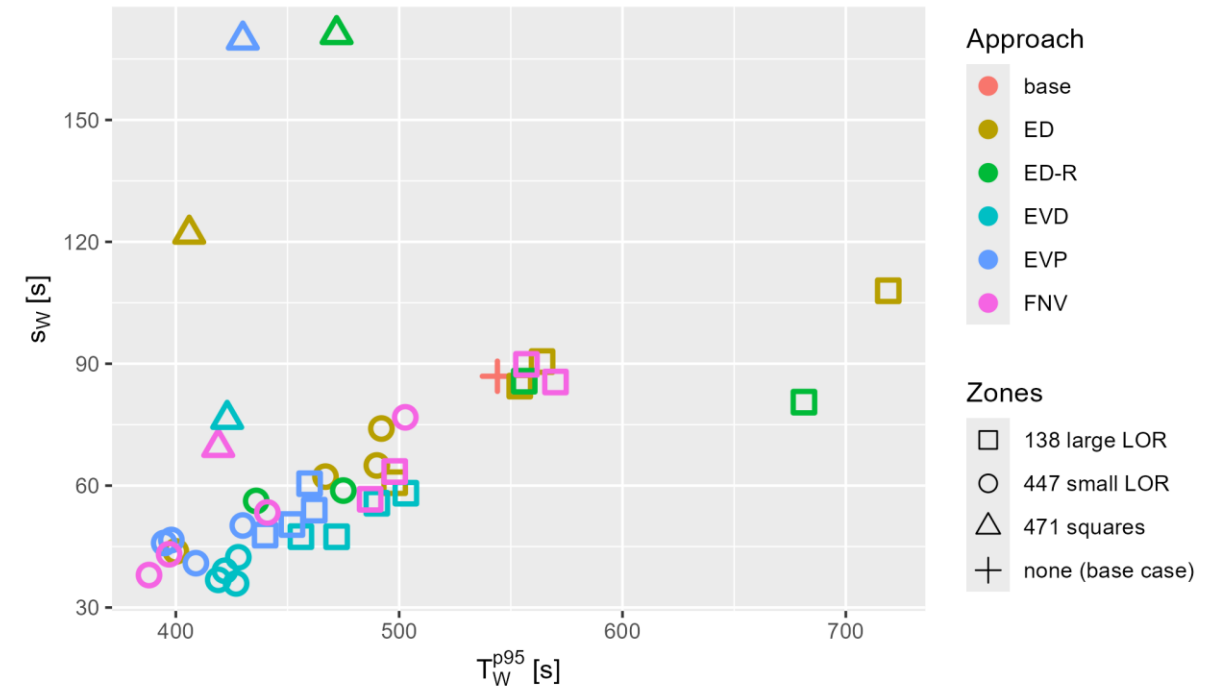
Approach	\bar{s}_w	n
base	86.9	1
ED	79.0	9
ED-R	90.5	5
EVD	48.8	9
EVP	62.9	9
FNV	64.0	9

s_w over demand



Source:[11]

s_w over 95th percentile of wait times T_W^{p95}



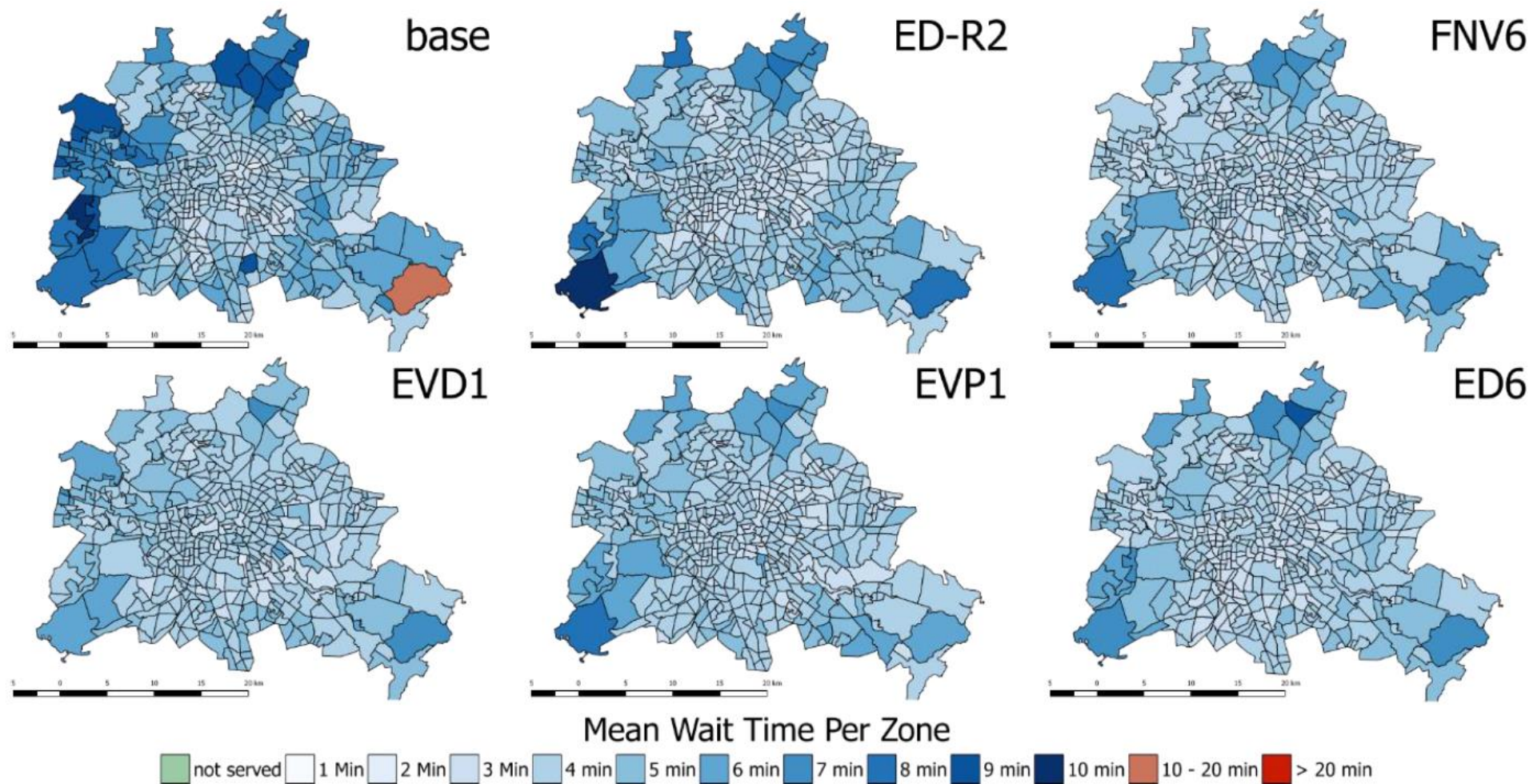
Source:[11]



Spatial Distribution of Wait Times



- **Base** = no rebalancing
- **ED** = estimated demand
- **FNV** = fixed number of vehicles
- **EVD** = equal veh. density
- **EVP** = equal ratio vehicles/population



Source:[11]

Key Findings regarding RQ 3

- Demand-anticipatory rebalancing can lead to unequal wait times for MoD services
- Other rebalancing approaches such as maintaining equal vehicle density can reduce the standard deviation of zonal mean wait times roughly by half
- Total realized demand increases in reaction to rebalancing by 20 - 40 %

Policy implications

- Profit-oriented MoD operators concentrate on city centers
- Demand responds to service quality
 - Poor service quality erodes trust and long term acceptance of new mobility concepts
- Careful planning (regulation) of MoD configuration is essential, if considered as part of public transport
 - A priori definition of service level
- Agent based simulations can inform policy making and system

Some aspects to improve for simulation:

- Account for taste heterogeneity in mode choice simulation
- Improve simulation procedures for situations with a discrepancy of supply and demand potential (small fleet sizes)

- **Outlook regarding autonomous Mobility-on-Demand:**
 - SAE Level 4 driving (SafeStream, KIRA, ...)
 - Transport-as-a-Service (IMoGer, ...)



Included publications



Publication 1:

Autonomous mobility-on-demand in a rural area: Calibration, simulation and projection based on real-world data

T. Schlenther, C. Lu, S. Meinhardt, C. Rakow, and K. Nagel
Case Studies on Transport Policy, page 101418, 2025a. ISSN 2213-624X.
doi: <https://doi.org/10.1016/j.cstp.2025.101418>



Publication 2:

The speed of shared autonomous vehicles is critical to their demand potential

T. Schlenther, and K. Nagel
World Electric Vehicle Journal, 16(8), Aug. 2025.
ISSN 2032-6653. doi: [10.3390/wevj16080447](https://doi.org/10.3390/wevj16080447).



Publication 3:

Addressing spatial service provision equity for pooled ride-hailing services through rebalancing

T. Schlenther, G. Leich, M. Maciejewski, and K. Nagel.
IET Intelligent Transport Systems, 17(3):547–556, Dec. 2023. doi: <https://doi.org/10.1049/itr2.12279>.



Thank you for your attention 😊

I would like to express my sincere gratitude to my co-authors:

- Chengqi Lu
- Christian Rakow
- Gregor Leich
- Kai Nagel
- Michal Maciejewski
- Simon Meinhardt



References and Image Sources



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- [2] Schlenther, T., Lu, C., Meinhardt, S., Rakow, C., & Nagel, K. (2025). Autonomous mobility-on-demand in a rural area: calibration, simulation and projection based on real-world data. *Case Studies on Transport Policy*, 101418.
- [3] Ziemke, D. Metzler, S. Nagel, K. (2019). Bicycle traffic and its interaction with motorized traffic in an agent-based transport simulation framework, *Future Generation Computer Systems*, Volume 97, Pages 30-40, ISSN 0167-739X, <https://doi.org/10.1016/j.future.2018.11.005>.
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- [6] Bischoff, J., Maciejewski, M., 2020. Proactive empty vehicle rebalancing for demand responsive transport services, *Procedia Computer Science* 170, 739–744. doi:10.1016/j.procs.2020.03.162.
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- [9] Ziemke, D. (2022). Person-centric integrated modeling of transport and urban systems. PhD Thesis. Technische Universitaet Berlin (Germany).
- [10] Schlenther, T., & Nagel, K. (2025). The Speed of Shared Autonomous Vehicles Is Critical to Their Demand Potential. *World Electric Vehicle Journal*, 16(8), 447.
- [11] Schlenther, T., Leich, G., Maciejewski, M., & Nagel, K. (2023). Addressing spatial service provision equity for pooled ride-hailing services through rebalancing. *IET Intelligent Transport Systems*, 17(3), 547-556.

Topic: **How system configuration shapes demand -**
Agent Based Simulation of Mobility-on-Demand
systems & policy insights

Date: 2025-11-28

Author: Tilmann Schlenther

Institute: DLR-VF-MSE

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