

Integrating micro-mobility availability information into MaaS for multi-modal trips

Project deliverable D2.1

WWW.SUM-PROJECT.EU



**Co-funded by
the European Union**

This project has received funding from
the European Union's Horizon Europe
research and innovation programme
under grant agreement No 101103646.

Deliverable Administrative Information

Deliverable Administration					
Grant Agreement	101103646	Project short name	SUM		
Deliverable no.	2.1	Deliverable Name	Integrating micro-mobility availability information into MaaS for multi-modal trips		
Status	Final	Due date	31/05/2024	Date	29/05/2025
Author(s)	Alessandra Scholl Sternberg (SIEMENS), Jingyi Cheng (TUD), Martijn Brautigam (TUD)				
Dissemination level	PU = Public				
Document history	Version	Date	Submitted	Reviewed	Comments
	V1.0	30/04/2025	Alessandra Scholl Sternberg (SIEMENS)	Shadi Sharif Azadeh (TUD), Luce Brotcorne (INRIA)	First Draft
	V1.1	28/05/2025	Alessandra Scholl Sternberg (SIEMENS)	Shadi Sharif Azadeh (TUD), Luce Brotcorne (INRIA), Giulia Petrarulo (INRIA)	Final Version

Legal Disclaimer

Co-funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Climate, Infrastructure and Environment Executive Agency (CINEA). Neither the European Union nor the granting authority can be held responsible for them.

Copyright © SUM Consortium, 2023.

TABLE OF CONTENTS

DELIVERABLE ADMINISTRATIVE INFORMATION	1
TABLE OF CONTENTS	2
PROJECT EXECUTIVE SUMMARY	3
DELIVERABLE EXECUTIVE SUMMARY	1
1.1 KEY WORDS	1
1.2 SUMMARY	1
1 LIST OF ABBREVIATIONS AND ACRONYMS	2
2 PURPOSE OF THE DELIVERABLE	3
2.1 ATTAINMENT OF THE OBJECTIVES AND EXPLANATION OF DEVIATIONS	3
2.2 INTENDED AUDIENCE	3
2.3 STRUCTURE OF THE DELIVERABLE AND LINKS WITH OTHER WORK PACKAGES/DELIVERABLES	3
3 SHARED FLEET AVAILABILITY PREDICTIONS FOR MULTI-MODAL TRIPS INTEGRATION IN MAAS	4
3.1 THE PREDICTION MODEL	4
3.2 DATA COLLECTION AND TRAINING THE MODEL	6
3.3 MODEL INTEGRATION INTO API, INCLUDING ARCHITECTURE	11
3.4 INTEGRATION INTO A MAAS TRAVEL PLANNER	12
3.5 NEXT STEPS	14
4 CONCLUSIONS	14
5 REFERENCES	15

Project Executive Summary

The objective of the SUM project is to transform current mobility networks towards innovative and novel shared mobility systems (NSM) integrated with public transport (PT) in more than 15 European Cities by 2026, reaching 30 by 2030. Intermodality, interconnectivity, sustainability, safety, and resilience are at the core of this innovation. The outcomes of the project offer affordable and reliable solutions considering the needs of all stakeholders such as end users, private companies, public urban authorities.

Social Media links:



@[SUMProjectHoEU](https://twitter.com/SUMProjectHoEU)



@[SUM Project](https://www.linkedin.com/company/SUM-Project)

For further information please visit WWW.SUM-PROJECT.EU

Deliverable executive summary

1.1 Key words

Multimodality, modal integration, scheduling optimisation, transfer optimisation, trip planning.

1.2 Summary

The format of deliverable 2.1 is "DEC" (Dissemination, Exploitation, and Communication Activities) type, therefore its primary focus should be on raising awareness, sharing knowledge, and outlining future plans rather than detailing technical implementation. It consists of (a) this document, which explains the tools developed for forecasting demand and availability of shared mobility services and their integration into MaaS travel planners, (b) the codebase for the forecasting demand model, and the API development (c) sample data for testing the models. The tools will be applied in Rotterdam and Munich, with a modular API developed by Siemens for integration into real-world applications.

List of figures

Figure 1 – Conceptual Framework of Free-Floating Shared Micro-Mobility System Dynamics. Illustrated using the CHECK e-scooter service from the Beurs, Rotterdam pilot study.

Figure 2 – Data collected for Beurs, Rotterdam and Großhadern, Munich pilot studies.

Figure 3 – Visualization of the target prediction area for Rotterdam Beurs mobility hub. Shows the geofencing zone, H3 hexagon, nearby tram stops, and metro entrances.

Figure 4 – Spatial distribution of daily average pick-up and drop-off demand within the Beurs area and central Rotterdam.

Figure 5 – MVG Bikeshare stations and pickup demand heatmap around Großhadern mobility hub.

Figure 7a – Integration of Fleet Availability Forecasts into a MaaS Platform for Real-Time User Information.

Figure 7b – Example of Fleet Availability Prediction Linked to a MaaS Trip Plan.

1 List of abbreviations and acronyms

Acronym	Meaning
API	Application Programming Interface
B2B	Business-to-business
B2C	Business-to-Consumer
EC	European Commission
GA	Grant Agreement
KPI	Key Performance Indicator
MaaS	Mobility as a Service
NSM	New Shared Modes
SUM	Seamless Urban Mobility
WP	Work Package

2 Purpose of the deliverable

2.1 Attainment of the objectives and explanation of deviations

The objectives related to this deliverable have been achieved in full and as scheduled/are on track to be fulfilled on schedule.

2.2 Intended audience

This deliverable is intended for a range of audiences within the SUM project and beyond. Key stakeholders include technical partners and developers involved in WP2 and WP3, city representatives and mobility planners participating in the Living Labs and Observer Cities, as well as policymakers and researchers interested in multimodal mobility integration. The content may also be of interest to MaaS providers, public transport operators, and shared mobility companies seeking to enhance real-time service integration within urban transport networks.

2.3 Structure of the deliverable and links with other work packages/deliverables

The primary objectives of T2.1 are to (i) develop and apply short-term forecasting of passenger demand for shared-mobility services; (ii) develop and apply short-term forecasting of shared-mobility fleet availability models, and; (iii) integrate the first two objectives (i) and (ii) into multimodal travel information provided to travellers provisioned as part of a MaaS travel planner.

3 Shared fleet availability predictions for multi-modal trips integration in MaaS

3.1 The prediction model

Modelling Goals

The objective of this task is to enable real-time, data-driven support for Mobility-as-a-Service (MaaS) application by developing a short-term forecasting pipeline for shared micro-mobility systems. This involves two key modelling steps: (1) Short-term forecasting of passenger demand for the shared micro-mobility service, (2) Short-term forecasting of shared-mobility service's fleet availability based on real time information. The predictive modelling framework is designed to be generalizable to different new-and-shared micro-mobility services and adaptable to new data received in the future.

The short-term predictive models trained via NSM services' historical data will be stored to train the model. During online application, short-term demand and fleet availability predictions are generated from the trained predictors with real-time inputs. These predictions are sequentially integrated into a MaaS multimodal travel planner via an API, allowing users to access timely and accurate availability information when planning their journeys.

To ensure suitability for real-world deployment, the predictive models must meet several practical requirements. First, they need to be computationally efficient, enabling rapid generation of predictions to support frequent updates within the MaaS application. Timely forecasting is essential for delivering accurate and up-to-date information to end users. Second, the models should be lightweight and resource-efficient, making them easier and more cost-effective to deploy in cloud environments. Simpler model structures reduce the engineering effort and costs associated with API integration and ongoing maintenance. Finally, as demand and availability patterns are subject to change over time, the models must be easily updatable and maintainable. This requires a design that supports regular retraining or fine-tuning using recent data, ensuring sustained accuracy with minimal overhead.

Problem definition: short-term demand and fleet availability forecasting

- **Short-Term Forecasting:**
This refers to the adaptive prediction of shared micro-mobility demand and service availability in the near future, using real-time information as input. These forecasts capture the ongoing dynamics of the system – such as current service availability and changing weather conditions – and are frequently updated to maintain accuracy. Typically, they cover short time intervals (e.g., the next 15 minutes to 1.5 hours), enabling responsive and data-driven decision-making for service management.
- **Pickup and Drop-off Demand of Shared Micro-Mobility Services:**
 - Pickup Demand: The number of vehicles picked up from a specific target area during a given time interval.
 - Drop-off Demand: The number of vehicles returned to the same target area during that time interval.
- **Fleet availability of Shared Micro-Mobility Services:**
 - In practice, the number of available vehicles in a shared micro-mobility system fluctuates dynamically due to ongoing pickup and drop-off activities. To account for this uncertainty, we represent expected fleet availability as a likelihood estimate. That is, we predict the probability that at least one vehicle (e.g., shared bike or e-scooter) will be available for rental within a specified area and time interval. This probabilistic measure reflects the system's ability to meet user demand in the near future.
- **Target Area for Forecasting:**
 - In free-floating micro-mobility services, a target area is defined as a polygon within the larger service region where pickups and drop-offs are tracked.
 - In dock-based services, the target area usually corresponds to a specific station where users collect or return vehicles.

Demand prediction

We develop a demand prediction model for both pickups and drop-offs that forecasts how many requests are expected within the target service region. Each demand prediction is generated for a specific future 15-minute intervals, covering the future 15 to 90 minutes ahead (i.e., 1-to-6 time intervals into the future). For each time step and each target to be predicted (pickup or drop-off), a dedicated model is trained independently for task-specific predictions.

The model enhances its demand forecasting accuracy by incorporating contextual features that capture both dynamic environmental influences and recurring usage patterns. One key source of information is weather conditions, which significantly impact bike and scooter usage (El-Assi et al., 2017). Previous studies have shown that demand tends to drop during cold, rainy, or humid weather, while warm, dry, and sunny conditions encourage more trips. In addition to weather, the model also accounts for seasonal and temporal patterns, such as the hour of the day and day of the week, which align with common travel behaviours related to commuting, leisure, and other routine activities. Additional contextual features, such as Point-of-Interest (POIs) and product specific information about the NSM services, can also be incorporated to further enhance model performance, depending on the specific use case (Lin et al., 2020).

We adopt XGBoost (Extreme Gradient Boosting) as the predictive model for short-term demand forecasting in shared micro-mobility services. XGBoost is a purely data-driven machine learning algorithm that builds an ensemble of decision trees optimized through gradient boosting. Its strength lies in its high predictive accuracy and robustness across various spatial and temporal settings, as demonstrated in prior studies on micro-mobility demand prediction (Schimohr et al., 2023). This makes it particularly suitable for dynamic urban environments, where demand patterns can fluctuate rapidly. In addition to its forecasting capabilities, XGBoost is highly efficient computationally. It can be quickly trained and deployed, requiring minimal processing power, which makes it ideal for real-time applications. Predictions can be generated within seconds, enabling frequent updates that support timely decision-making in operational systems. The model is also lightweight and easy to maintain, facilitating integration with cloud-based services and APIs. This balance of performance and practicality makes XGBoost a well-suited choice for both research and industry applications in the context of Mobility-as-a-Service (MaaS).

Upon request, the model generates demand forecasts for the next six-time intervals (covering the next 15 to 90 minutes). These predictions support real-time operational planning and can be updated frequently as new data becomes available.

Availability prediction

In this task, fleet availability is modelled as the probability that at least one vehicle will be available for a passenger arriving at a specific future time interval. Similar to the demand forecasting setup, we train a set of six XGBoost regression models for each service region, with each model responsible for predicting one of the six future 15-minute intervals (up to 90 minutes ahead). Each model outputs a non-negative value, interpreted as the probability (e.g., x%) that a vehicle will be available. This continuous probability can then be translated into qualitative availability labels for end-user communication. In our case, we apply a thresholding approach: probabilities above 75% are labelled as “Very Likely”, between 50%-75% as “Likely”, 25%–50% as “Less Likely”, and below 25% as “Unlikely”.

The prediction model incorporates both contextual and operational inputs. Contextual features include time-related variables (e.g., hour of the day, day of the week) and weather conditions (e.g., temperature, precipitation, wind speed, wind gusts). Operationally, fleet availability is influenced by user behaviour – specifically, future pickup and drop-off events – and the initial number of available vehicles in the region. Therefore, the model takes as input the forecasted pickup and drop-off demand (generated by the demand prediction models) along with the starting fleet count, allowing it to dynamically estimate future availability.

Model Hyperparameter Selection

To optimize model performance, we apply randomized hyperparameter search using 5-fold cross-validation, ensuring robust generalization across different data subsets. This approach balances search efficiency with

model reliability. The predictive performance of the trained models is evaluated using two standard error metrics: Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), which provide insight into both average prediction accuracy and sensitivity to larger errors.

3.2 Data collection and training the model

Mobility Hub Selection, Selected NSM, and Data Collection

Mobility Hub Description – Beurs, Rotterdam

Located in the heart of Rotterdam, the Beurs Mobility Hub serves as a central node connecting various transportation modes and catering to a diverse urban population. Situated near prominent Points of Interest (POIs) such as shopping centres, business districts, and cultural venues, it facilitates seamless movement for both residents and visitors. Beurs is a pivotal interchange for Rotterdam's public transportation network, integrating tram, bus, and metro services.

The area around Beurs is equipped with dedicated bike lanes and designated parking zones for micro-mobility devices. This infrastructure supports safe and convenient use of bicycles and e-scooters, encouraging sustainable urban travel. The hub offers a range of shared mobility options, including bicycles, e-scooters, and electric mopeds. These services are provided by operators like Donkey Republic (bicycles), Lime (e-bikes), and Check (e-mopeds), enhancing first- and last-mile connectivity for users.

Mobility Hub Description – Großhadern, Munich

Located in the southwestern district of Hadern in Munich, the Großhadern Mobility Hub serves as a significant transportation node for the local community. The area encompasses several popular POIs, notably the Klinikum Großhadern, a major hospital affiliated with Ludwig Maximilian University of Munich, and various residential neighbourhoods. This hub caters to the mobility needs of both the hospital's staff and visitors, as well as local residents. The hub is well-integrated into Munich's public transportation network. The Großhadern U-Bahn station, served by the U6 line, provides direct subway access to central Munich and other districts. Additionally, multiple bus routes, including lines 56, 266, 268, and 269, connect the area to surrounding neighbourhoods and key locations, ensuring comprehensive transit accessibility.

Munich has invested significantly in cycling infrastructure, and Großhadern benefits from this commitment. The district features dedicated bike lanes that promote safe and efficient cycling. Secure bicycle parking facilities are available near public transport stations, encouraging the combination of cycling with other modes of transit. Currently, the Großhadern area offers various shared mobility services to enhance connectivity and provide flexible transportation options. These services include bike-sharing program by Münchner Verkehrsgesellschaft (MVG)/SVM, facilitating convenient short-distance travel within the district.

Collaborated New-and-Shared Micro-Mobility Services

- **Beurs, Rotterdam – CHECK shared e-scooter service**
 - **NSM Service Information:** CHECK is a privately-owned shared e-scooter service provider that has been active in Rotterdam since June 2020. Operating under a free-floating model, the service allows users to rent and return scooters anywhere within the designated service area. CHECK runs 24/7 and is fully app-based to offer a seamless rental experience. Additionally, the service has been connected to the RET (Rotterdam's local public transport provider) app, enabling users to view nearby CHECK scooters available for pickup via the map function. The pricing of CHECK includes a base unlock fee followed by a per-minute usage rate, making it a flexible and convenient last-mile mobility option for urban travellers.

Figure 1 below illustrates the interaction between user demand and service operations in a free-floating shared micro-mobility system. From the user perspective, environmental factors – such as weather, public transit access, and nearby POIs – influence trip requests and the distribution of fleet in the city. From the service provider's perspective, tracking how pick-up and drop-off events dynamically affect fleet availability is crucial. When supply is insufficient

and no vehicles are available, user demand goes unmet, leading to a poor user experience and potentially discouraging long-term use of the service.

Background – Free-Floating Shared Micro-Mobility

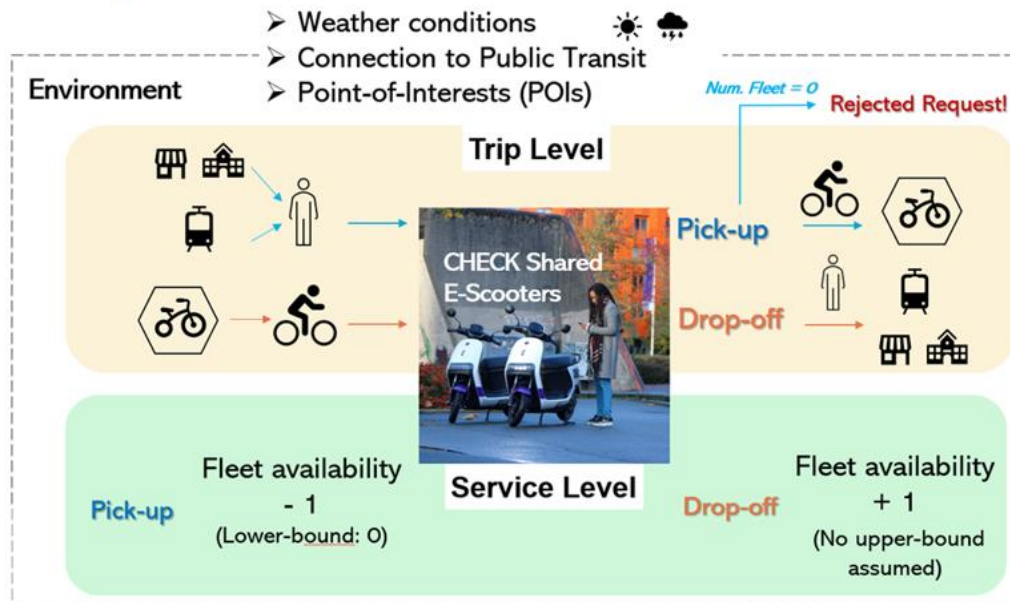


Figure 1 **Conceptual Framework of Free-Floating Shared Micro-Mobility System Dynamics**. Illustrated using the CHECK e-scooter service from the Beurs, Rotterdam pilot study.

- **Received NSM Data:** The data we received from CHECK covers activities related to the Beurs area between 12 January 2022 and 30 January 2024. It includes historical trip data for trips where the pickup or drop-off occurred within the Beurs area. Each record contains the vehicle ID, starting and ending datetimes and coordinates, and a description specifying whether the trip started or ended at Beurs. Additionally, we received historical fleet availability snapshots, taken once per hour, each capturing the snapshot datetime along with detailed information on idle vehicles, including their locations and remaining battery levels. This dataset enables focused forecasting analyses of user demand and fleet availability for the CHECK service within the Beurs area.
- **Supporting information:** To analyse overall public transit demand in Rotterdam, RET provided historical origin-destination data for all public transit stops and stations connected to the Beurs mobility hub, where Beurs serves as either the trip origin or destination. The data includes hourly aggregated trip counts from the same historical period as the NSM dataset. Additionally, historical weather data was retrieved via the open-source API [Open-Meteo](https://open-meteo.com/)^[1] to support demand forecasting. Point-of-Interest (POI) data was also collected for the Beurs mobility hub area to better understand its functionality and the factors influencing local travel demand.

^[1][Open-Meteo](https://open-meteo.com/): an open-source historical weather data API, <https://open-meteo.com/>

- **Großhadern, Munich – MVG/SVM Bikeshare service**

- **NSM Service Information:** MVG Bikeshare (MVG Rad) is Munich's public bike-sharing service, operated by Münchner Verkehrsgesellschaft (MVG). The system offers bike rental service throughout the city centre of Munich and its suburb districts, including Großhadern. Bikes are available 24/7 and can be accessed via the MVGO app, which displays nearby bikes available for rental. The standard rate is €0.09 per minute, with a daily maximum of €12. Students at participating universities and IsarCard (Munich's regular public transit pass) subscribers benefit from discounted rates. The service operates on a hybrid model, with both

- fixed stations and free-floating options, allowing users to return bikes either to designated stations or within specified areas.
- **Received NSM Data:** For the Munich case study centred around the Großhadern mobility hub, various datasets were collected to support the analysis of shared micro-mobility and public transit demand. From the MVG shared mechanical bike service, trip data was obtained to assess usage patterns. The raw trip data contains one dataset for each station within area of interest per day between 2022-06-01 and 2023-10-31. Number of bikes available is only present for dates after 2023-01-01.
 - **Supporting information:** In terms of public transportation, aggregated hourly check-in and check-out data were collected, along with estimated passenger counts at the vehicle level, capturing both boarding and alighting activity. Additionally, weather data and Point-of-Interest (POI) information for the surrounding area were gathered to better understand contextual factors influencing travel behaviour.

Figure 2 below summarizes all the data collected for Beurs, Rotterdam and Großhadern, Munich pilot studies.

	New & Shared Micro-Mobility	Public Transport	Contextual Info.
Beurs – Rotterdam LL.	CHECK – Shared E-Scooters • Trip data • Per hour fleet availability data	Hourly public transit demand between <u>Beurs</u> mobility hub and other stations in Rotterdam	• Point-of-Interest data for Beurs area • Weather data
Großhadern – Munich LL.	MVG – Shared Mechanic Bikes • Trip data	• Aggregated hourly check-in and check-outs • (Estimated) passenger count data at vehicle level (boarding and alighting data)	• Point-of-Interest data for Beurs area • Weather data

Figure 2 Data collected for Beurs, Rotterdam and Großhadern, Munich pilot studies.

Short-term Forecasting Model Calibration for Rotterdam Living Lab

Geographical area division (hexagons)

- **H3 indexing:** In the Rotterdam case study, the CHECK shared e-scooter service operates under a free-floating model. To analyse fleet availability around the selected mobility hub *Beurs*, we first divide the service area into predefined geographical units using the H3^[1] spatial indexing method. This method partitions the map into hexagonal cells at a specified resolution. For this case study, we use H3 resolution level 9, which corresponds to cells covering approximately 0.74 square kilometres each, with an edge length of about 174 meters.
- **Facilities - NSM Parking and Nearby Public Transit Services:** The Rotterdam Beurs mobility hub is well-connected with both metro and tram public transit services, providing convenient access to and from the NSM Parking facility. As shown in Figure 3, several tram stops (blue) and metro exits/entrances (red) are located within a short walking distance around Beurs. The target H3 hexagon (gray) highlights the core coverage area, while the surrounding green geofencing zone represents the planned mobility management area for 2025. Together, these facilities ensure seamless multimodal connections, supporting efficient first- and last-mile travel for users accessing NSM Parking and the broader Beurs area.

^[1]Uber H3 indexing system, <https://h3geo.org/>

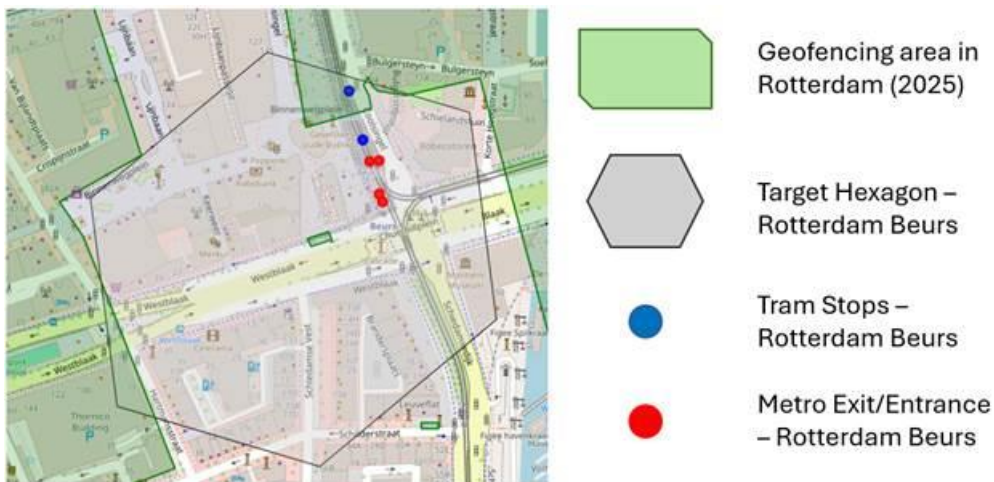


Figure 3 Visualization of the target prediction area for Rotterdam Beurs mobility hub. It shows the current geofencing zone (green polygon), the target H3 hexagon covering Beurs (gray), nearby tram stops (blue dots), and metro exits/entrances (red dots).

The maps in Figure 4 show the daily average pickup (left) and drop-off (right) demand per H3 grid cell within the Beurs mobility hub area (highlighted as the target h3 grid) and other grids in the central area of Rotterdam. Colour intensity indicates the magnitude of demand, with darker shades representing higher average trip counts. Compared to other grids on the map, the Beurs H3 grid exhibits the highest daily average pick-up and drop-off demand in the analysed area of Rotterdam.

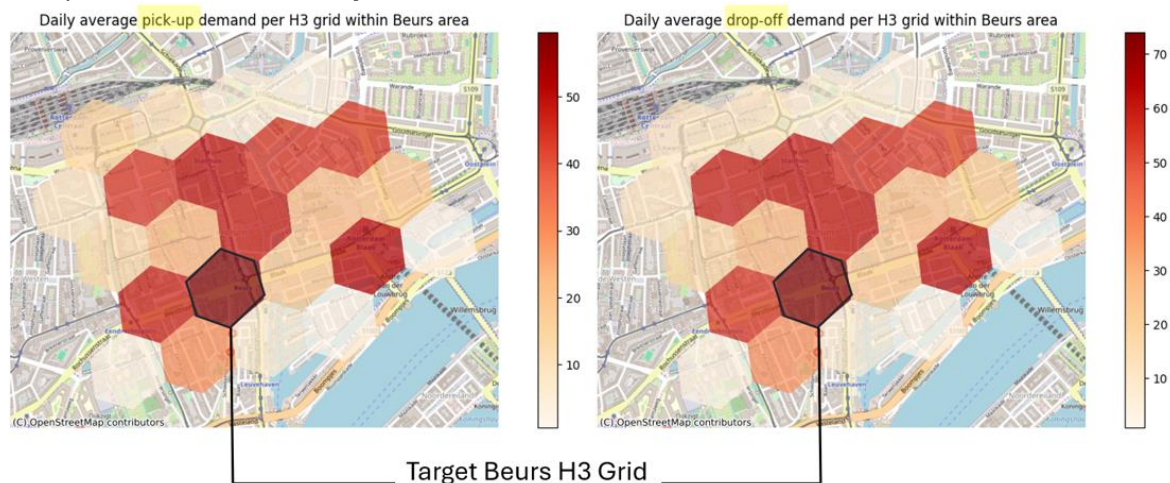


Figure 4. Spatial distribution of daily average pick-up and drop-off demand within the Beurs area, and the center of Rotterdam areas

Data Pre-processing and Model training

In this task, the real-time forecasting API focuses exclusively on predicting demand and availability within the target H3 grid covering the Beurs mobility hub area, although the same functionality can be extended to other grids of Rotterdam in the future. To enable model training, historical trip data, fleet availability records, and weather information are first pre-processed using the procedure outlined below.

- **Historical trip data:** The raw trip data is first separated into two datasets, pick-up and drop-off records, each capturing the corresponding activity over time. These records are then filtered to retain only those that occurred within the target H3 grid, based on the geographic coordinates of the pickup or drop-off location. A 15-minute interval time series is created for each H3 grid by aggregating trip counts within each time window, covering the historical period from January 22, 2022, 00:00–00:15 to January 30, 2024, 23:45–00:00.

- Fleet availability data: The original fleet availability data consists of hourly snapshots showing the number of idle scooters across the Rotterdam area. To extract availability for the Beurs mobility hub, we identify the number of idle vehicles located within the target H3 grid at each snapshot time. To capture fleet dynamics at a finer temporal resolution, historical pickup and drop-off records are used to reconstruct the sequence of events affecting fleet size within the grid. This approach allows us to estimate the fleet size at 15-minute intervals throughout the historical period. For each interval, we compute the percentage of time that at least one scooter was available, called 'availability likelihood'. This value is then used as the target variable for fleet availability forecasting.
- Weather data for the Beurs mobility hub area was retrieved from the Open-Meteo API, with hourly updates covering the entire historical period.

In the Rotterdam pilot study, fleet availability is predicted for the next 90 minutes in 15-minute intervals (six steps ahead). As outlined in the model design, pick-up and drop-off demand predictors are first trained to forecast demand for each interval. These predictions, combined with weather data (temperature, wind speed, and precipitation), are then used to estimate future fleet availability at the Beurs mobility hub. The models are trained on the first 554 days of data, representing approximately 75% of the total dataset. The remaining 185 days (25%) are used for validation, covering the final portion of the study period.

Predictive Model Performance: Short-Term Demand and Fleet Availability Forecasting

The forecasting models are validated on the testing dataset, with emphasis on both predictive accuracy and computational speed. Validation results show that all models can generate next-step predictions in under 0.1 second, demonstrating the ultra-fast response time necessary for real-time forecasting applications.

For the Beurs mobility hub's target H3 grid, the average MAE for future pickup demand forecasting is 0.195, and the RMSE is 0.416 across all future time intervals for the 6-step ahead forecasting tasks. For drop-off demand, the average MAE is 0.756 and RMSE is 0.971, indicating that drop-off demand is slightly more challenging to predict accurately within the same forecasting framework. Implementing SHAP for feature importance analysis, we find the model consider temporal seasonal features 'hour-of-the-day' and 'day-of-the-week' to be the most important input features, followed by the weather features.

For availability likelihood forecasting, predicted demand values from the trained pickup and drop-off models are first used as inputs to the fleet availability predictor. Combined with the initial fleet size in the target grid, the model delivers high-accuracy predictions. For the 1st through 6th step-ahead forecasts (in 15-minute intervals), the MAEs are 4.352%, 7.918%, 10.361%, 11.017%, 11.900%, and 12.115%, respectively. Corresponding RMSEs are 11.691%, 18.450%, 22.325%, 23.185%, 24.833%, and 25.026%. A SHAP-based feature importance analysis shows that the initial fleet size is the most influential input, followed by drop-off and then pickup demand predictions.

Short-Term Forecasting Model Calibration for Munich Living Lab

The predictive framework used in the Rotterdam case can be extended to the Munich pilot study at the Großhadern mobility hub. For the shared mobility component, trip data from MVG's shared mechanical bike service provides the basis for modelling pick-up and drop-off demand. Figure 5 displays a heatmap of pick-up demand in Großhadern over the data period, with the two MVG Bikeshare stations highlighted. The station located at the top of the map offers 10 parking spaces, while the bottom station is larger, with 15 parking

spaces and historically a higher available fleet size.

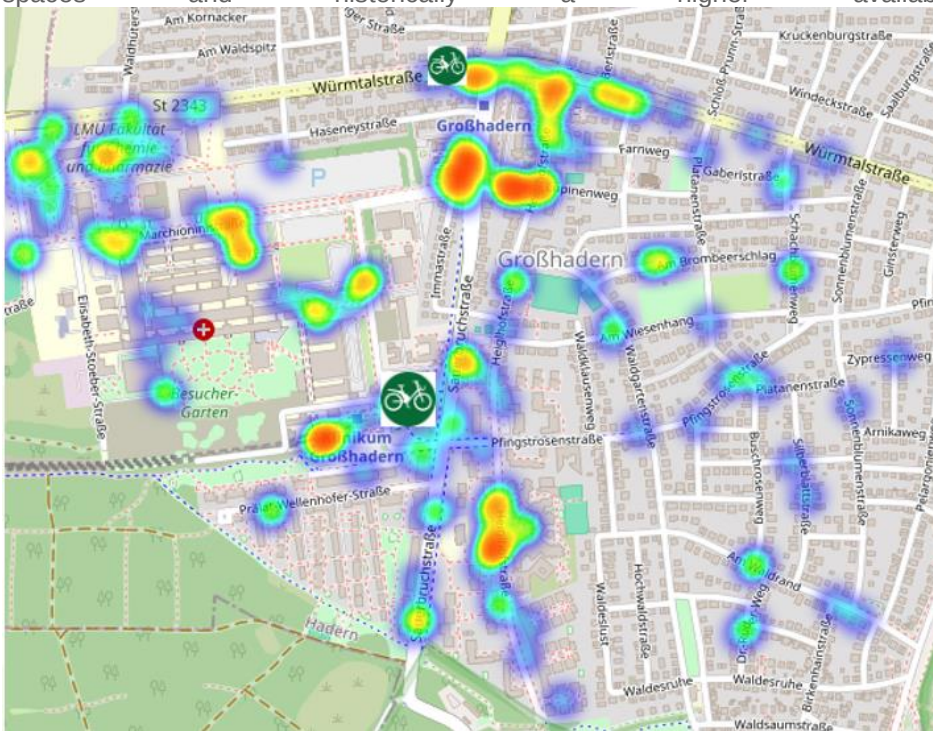


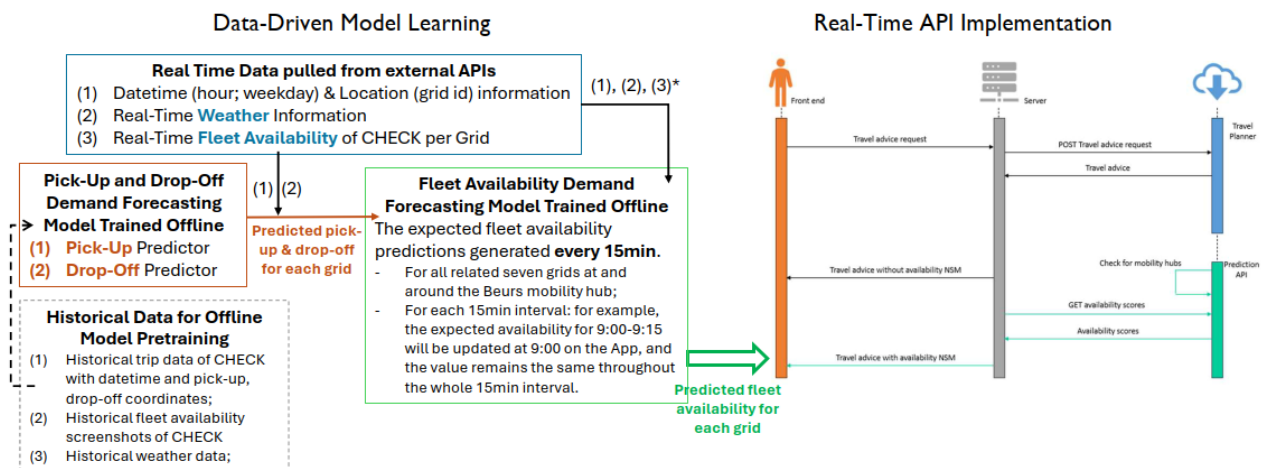
Figure 5 MVG Bikeshare stations and pickup demand heatmap around Großhadern mobility hub.

As in Rotterdam, the Großhadern mobility hub area can be divided into a group of H3 hexagonal grids, with each grid serving as a spatial unit for generating demand and availability forecasts. To enrich model inputs, weather data and Point-of-Interest (POI) information for the Großhadern area can be incorporated to capture contextual factors influencing mobility behaviour. After pre-processing the trip and contextual data into consistent time series formats (e.g., 15-minute), predictive models can be trained following the same approach used in Rotterdam, leveraging the designed multivariate XGBoost predictive framework. Once trained, the models can be deployed for real-time inference via Siemens Mobility API, enabling timely and location-specific forecasts in Großhadern mobility hub.

3.3 Model integration into API, including architecture

To enable real-time access to the short-term fleet availability predictions developed by TUD, Siemens designed and implemented a robust API infrastructure that integrates the trained predictive models into a scalable and responsive backend environment. The core objective of this API layer is to serve fleet availability forecasts – updated every 15 minutes – directly to front-end applications such as the MaaS travel planner.

Data – Model – API Pipeline



The API architecture follows a modular, cloud-based design, allowing for seamless interaction between prediction services, data pipelines, and client applications. As illustrated in the figure above, the pipeline comprises two main stages: data-driven model learning and real-time API implementation.

API Architecture Overview

Backend services are responsible for ingesting real-time data (datetime, weather, fleet availability), running the predictive models trained by TUD, and storing the resulting availability forecasts per grid.

Prediction endpoints expose the fleet availability estimates via Rest APIs. These endpoints return, for each 15-minute interval and geographic grid:

- the availability prediction
- the timestamp of forecast validity

The request flow begins when a user interacts with the MaaS front-end, for example through the MaaS app, and initiates a travel request. In response, the travel planner triggers a call to the Siemens-hosted API to check for shared fleet availability at relevant locations. The API returns predicted availability values per grid and per time interval, specifically the probability that at least one shared vehicle will be available. These predictions are then used by the MaaS planner to refine route suggestions and present the user with an up-to-date, multimodal travel plan that includes shared mobility options where applicable.

The first implementation of the API and integration pipeline will be applied in the two living lab cities: Rotterdam and Munich. In Rotterdam, the system connects with the CHECK shared e-scooter service and integrates into the RET MaaS travel planner. In Munich, it interfaces with the MVG bike-sharing system. These two pilots serve as testbeds for validating the performance, scalability, and user value of the real-time availability forecasts within active multimodal travel environments.

3.4 Integration into a MaaS travel planner

The integration of the fleet availability prediction API into the RET MaaS travel planner involved a series of coordinated steps between Siemens and RET. Together, the teams began by defining the relevant mobility hubs within the city of Rotterdam, with Beurs selected as the first pilot location. Beurs was chosen due to its central position, multimodal connectivity, and active usage of shared mobility services, and therefore enough data for the availability predictions.

In the RET app, the routing logic is being updated to detect when a user's travel request passes through or terminates at a designated mobility hub such as Beurs. When this condition is met, the app triggers a request to the Siemens-hosted API to retrieve predicted availability data for shared mobility services in the surrounding area. This real-time information is then used to inform the journey planner, allowing it to prioritize and present multimodal routes that include shared options with high availability. Figure 7a illustrates how real-time fleet availability likelihood is predicted, integrated into the RET app via API, and presented to passengers during trip recommendation requests. Figure 7b provides a usage example to offer a tangible understanding of the end-user experience.

Providing real-time fleet availability predictions encourages seamless travel by helping passengers confidently plan transfers between public transit and shared micro-mobility services. This integration strengthens the complementary role of NSM, offering flexible first- and last-mile options that extend the reach, convenience and resilience of urban public transit network.

Maas with Fleet Availability Predictions

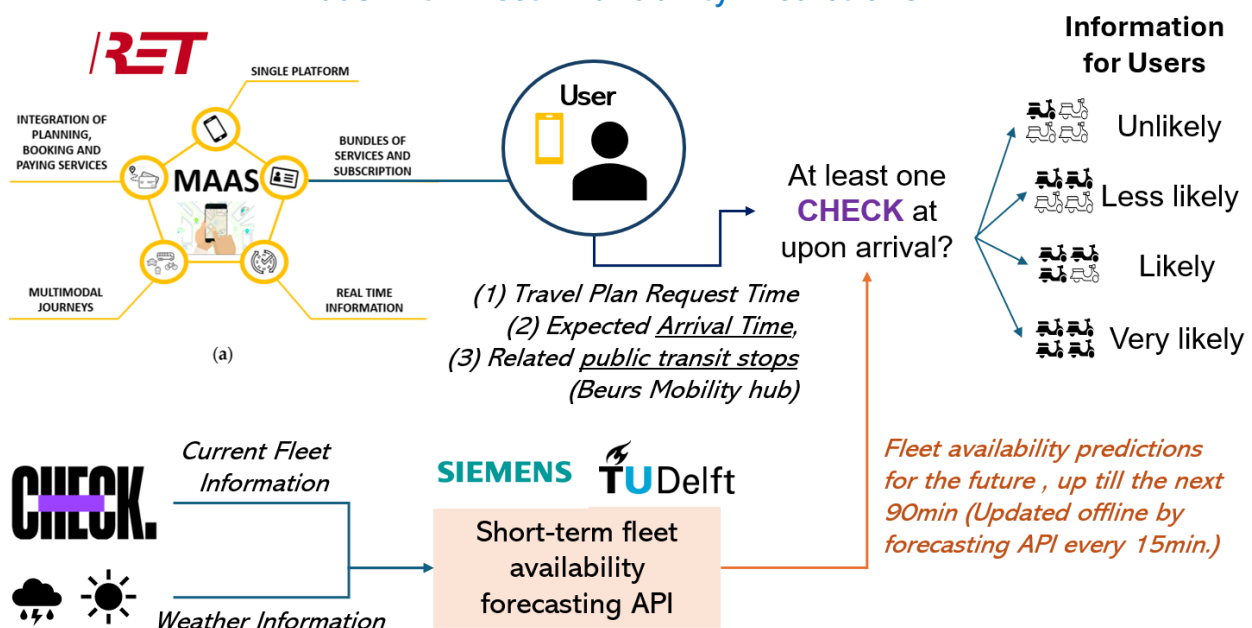


Figure 7.a Integration of Fleet Availability Forecasts into a MaaS Platform for Real-Time User Information. This figure presents how short-term fleet availability predictions are integrated into a MaaS system to inform users about the likelihood of finding at least one available CHECK e-scooter upon arrival at the Beurs mobility hub. The prediction pipeline combines real-time fleet and weather data to forecast availability for the next 90 minutes. These forecasts are generated by a short-term availability prediction API, updated every 15 minutes, and translated fleet availability likelihood predictions into user-friendly labels: Very likely, Likely, Less likely, or Unlikely. This information is incorporated into RET's MaaS platform to enhance travel planning with real-time micro-mobility insights.

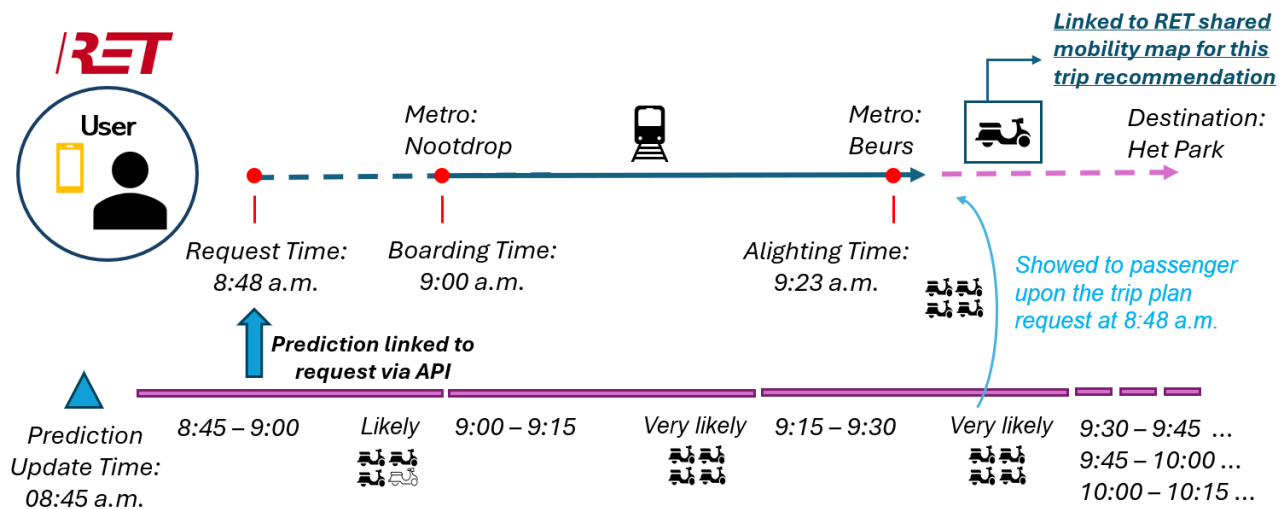


Figure 7.b Example of Fleet Availability Prediction Linked to a MaaS Trip Plan. This figure illustrates how short-term fleet availability predictions are integrated into the RET MaaS platform. The predicted availability likelihood icon is displayed to the passenger within the recommended trip in the app (top row), utilizing the real-time forecasting generated through the backend prediction process (bottom row).

3.5 Next Steps

The model and API will be calibrated for Munich as a preparation for the future implementation. The API is easily adaptable to be implemented in further cities, as long as data is available. The integration in MaaS apps of course differs depending on the current solution in each city.

4 Conclusions

The work carried out in Task 2.1 demonstrates the steps towards a successful integration of short-term fleet availability predictions into a MaaS travel planner, bridging advanced data-driven forecasting with real-world user applications. Through the collaboration between TUD, Siemens, and RET, the predictive models have been embedded into an API infrastructure that will enable timely, location-specific availability data to be presented directly to travellers at the moment of decision-making.

While the initial implementation is focused on the Beurs mobility hub in Rotterdam, the architecture and methodology have been designed with transferability in mind. The modular API structure, combined with the flexible grid-based prediction models, allows for adaptation to different cities, mobility hubs, and shared service providers. In the long term, the ambition is to make the API available to other living lab cities and observer cities within the SUM project. This will support a broader shift toward integrated, data-informed mobility ecosystems across Europe.

By improving the predictability and visibility of shared mobility options within multimodal journey planning, the tools developed in Task 2.1 contribute directly to increasing the attractiveness and usage of both shared modes and public transport. Ultimately, this supports the overarching project goal of building more sustainable, efficient, and user-friendly urban mobility systems.

5 References

1. El-Assi, W., Salah Mahmoud, M., & Nurul Habib, K. (2017). Effects of built environment and weather on bike sharing demand: a station level analysis of commercial bike sharing in Toronto. *Transportation*, 44(3), 589-613.
2. Schimohr, K., Doeblner, P., & Scheiner, J. (2023). Prediction of bike-sharing trip counts: Comparing parametric spatial regression models to a geographically weighted XGBoost algorithm. *Geographical Analysis*, 55(4), 651-684.
3. Lin, P., Weng, J., Hu, S., Alivanistos, D., Li, X., & Yin, B. (2020). Revealing spatio-temporal patterns and influencing factors of dockless bike sharing demand. *Ieee Access*, 8, 66139-66149.
4. Author (2000). Title. Etc