Street Art & Urban Creativity | Vol. 11, No. 7, 2025 | ISSN 2183-9956
Street Art & Urban Creativity. Scientific Journal
https://doi.org/10.62161/sauc.v11.6017

MODELLING AND ANALYTICS TOOLS FOR ELECTRIC MOBILITY

USE-CASES AT THE URBAN LEVEL

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KEYWORDS
Transportation
Electric vehicles
Electric mobility
Flexibility
Data
Vehicle-to-Grid
Models
Digital tools
DLR-MobilityLab

ABSTRACT
The integration of the transportation and electricity sectors presents both a challenge and an opportunity for the European energy system. On the one hand, large amounts of electricity are needed to power the electric vehicles, thereby, requiring a more accurate prediction of the demand in short-term and in the future. On the other hand, utilizing the Vehicle-to-Grid technology can provide grid services. Designing, management, and planning of the infrastructure requires sophisticated data-driven tools. This paper highlights a selection of the existing tools of the DLR (German Aerospace Center) developed for the modeling and analysis of the integrated electric mobility sector.

RECEIVED: 04 / 09 / 2025
ACCEPTED: 01 / 10 / 2025

1. Introduction

The integration of the transportation and electricity sectors presents both a challenge and an opportunity for the energy system. On the one hand, large amounts of electricity are needed to charge electric vehicles, thereby, requiring a more accurate prediction of the charging demand in the short term and strengthening the existing electricity infrastructure in the long term. According to the European Automobile Manufacturers' Association (ACEA), in 2023 there were an additional 150.000 public charging points installed, which brought the total in Europe to over 630,000 for the three million battery-electric vehicles (BEVs). To reach the 55% greenhouse gas emission reductions from the European Union by 2030, a total of 3.5 million charging points will be required (ACEA, 2024). This objective would require nearly three times the rate of installation achieved in 2023, on average, in the remining years. On the other hand, energy stored in the electric vehicles can be discharged back to the grid, utilizing the Vehicle-to-Grid (V2G) technology, to provide services, such as peak shaving and stabilizing the local networks. Considering the growing electric vehicle market in Europe (EC, 2019; EC, 2021; EC, 2023), and its challenges and opportunities, designing, management, and planning of the supporting electricity infrastructure for both charging and discharging applications requires sophisticated data-driven tools.

Predicting future electric mobility scenarios in terms of both energy and mobility in the urban context can be crucial in making the right decision and steps toward reaching carbon-neutrality goals in the EU. In the case of local energy management, accurate energy forecasting and quantification of flexibility from the electric vehicles is critical for the operation and planning of a stable electric network in the future (Gonzalezet al., 2019).

Technological innovation in the field of artificial intelligent and in particular machine learning methods handling energy management and planning is revolutionizing how smart city managers and planners are approaching some of their day-to-day challenges, as well as implementing strategies for long-term infrastructure planning. According to Yaghoubi et al., machine learning techniques (and in particular deep learning models, a sub-set of machine learning) are emerging as viable techniques within the domain of electric vehicle predictive analytics (Yaghoubi, 2024). Infrastructure planning in this context involves five dimensions of modeling and computation, charging demand prediction, optimization of charging station location, charging station utilization factor, charging scheduling and pricing (Deb, 2021).

Furthermore, research to date has shown that the integration of electric vehicles in the energy system is critical for both a sustainable transportation system as well as a sustainable energy system. Rana et al. conducted a review on the impact of EVs on electricity grids (Rana, 2025). The authors found that EVs can help balance out the electricity grid oscillations due to the unpredictability of the power grid. In another paper, Yang et al. explore the mitigation effects of EVs on the power grid due to extreme weather events (Yang, 2025). Their work proposes an assessment to analyze grid vulnerabilities. Similar work on the impact of EVs on power grids has been conducted by Sayed et al., (2022) Garwa and Niazi (2019) and Khalid et al. (2024), thus illustrating the central importance of this topic.

1.1. Theoretical Framework (the research question & literature review)

As outlined above electric vehicles are central to the transition of both the transportation and energy sectors as well as achieving sustainability objectives. While the above sources illustrate the breadth of research conducted on this topic, implementation within the real-world remains elusive (Clarke *et al.*, 2022). Thus, while ample scientific research is published, we see a disconnect when it comes to implementation. This is particularly the case for the transportation sector (Kervall & Pålsson, 2022; Khurshid et al., 2023; Kirjavainen & Suopajärvi, 2025). Consequently, there is a need to transmit academic research results into practice in a timely and efficient manner. In order to do this, the authors examine a new framework for presenting research to decision makers in the form of a mobility lab, which allows for interaction with models, data and various tool. These tools and the mobility lab itself are presented later in the paper.

An important requirement for developing such data-driven models and simulation tools is the availability of large amount of data from the field. In the case of real-time monitoring of the system, it is apparent that not only historical data, yet dynamic data from the smart IoT devices should be utilized as the input to such complex models. The availability of data from the APIs (application programming interfaces) enables seamless integration and streaming of dynamic data from the system for more up-to-date and accurate simulation and analytics of the electric mobility system in operation.

1.2. DATAMOST and MoDa: Research tools for decision-makers

Ensuring the successful transition to a sustainable transportation and energy system requires not only new technologies, but also user acceptance and an understanding of the tradeoffs. Thus, research plays a key role in exploring different outcomes by analyzing various scenarios. To do this, vast amounts of data and state-of-the-art models can be used to determine different scenarios and courses of action. At DLR (German Aerospace Center) two such projects highlight the role of research in enabling stakeholder involvement in planning and decision making. These projects are "Data and Model-based Solutions for the Transformation of Mobility" (DATAMOST) and “Models and Data for Future Mobility_Supporting Services” (MoDa) (DLR, 2022; DLR, 2025).

These projects draw on DLR’s extensive data resources and models to develop new services that help accelerate the shift toward more sustainable mobility. To effectively drive forward the mobility transition, these services must be practical, user-friendly and tailored to the specific needs of businesses and public institutions. A key element in developing scientifically robust methods and tools is taking advantage of cross-institute expertise within DLR.

The MoDa services will develop relevant and, most importantly, accurate scientific tools to provide insights for key customers such as local governments, national government, businesses, and the general public. They will cover a broad range of transport issues and work closely with potential stakeholders (DLR, 2025).

This paper highlights a selection of the existing scientific tools of the DLR that are specifically developed for the modeling, simulation and analysis of the integrated electric mobility systems in the urban context. These state-of-the-art tools enable European city’s energy and mobility stakeholders, including the energy utilities, charge point operators, city planners and managers among others to make date-informed decisions in a short- and long-term horizon by providing a platform for creating digital twins of the electric mobility systems, building different scenarios and generating analytics and solutions.

1.3. About the DLR

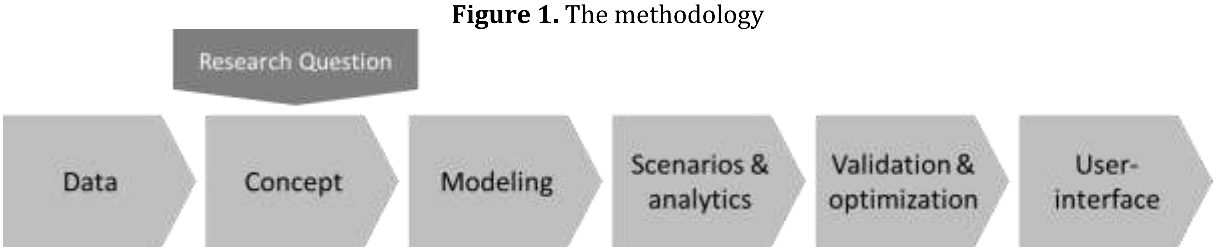
The DLR is the German Aerospace Center (in German: *Deutsches Zentrum für Luft- und Raumfahrt)*. It is a research organization working in five areas: space, flight, security, transportation, and energy. DLR serves as the national space center for Germany (DLR, 2025b).

Among 54 institutes of the DLR, two institutes, namely, the DLR Institute of Transport Research (DLR VF) and the Institute of Networked Energy Systems (DLR VE), contribute to this paper. The Institute of Transport Research focuses on all aspects of ground-based transit with a focus on sustainable transportation ranging from social to environmental issues. The scientific staff has diverse backgrounds (engineering to psychologist) to understand all the complex aspects of transportation and mobility in the twenty-first century (DLR, 2025c). At the DLR VE the focus lies on the transition to a sustainable energy system. To do this, the colleagues build energy models, model electricity grid, and model energy demand from numerous sources (including transportation). Experts at DLR VE also work to create scenarios of future energy use and utilization (DLR, 2025d).

2. Methodology

The MoDa services as described in the introduction section are rooted within the DLR’s scientific modeling and analysis activities. The scientific modeling and analysis in their standard form start from framing the right research questions related to the mobility landscape, then followed by creating computational models representing the complex system under the study and formulating sound scenarios for the detail analysis and of the foreseen objectives. In the special case of MoDa services, the standard scientific modeling and analysis approach is further enhanced and extended in the form of creating user tools to offer the opportunity to a wider spectrum of stakeholders beyond the conventional scientific community to access and utilize the produced scientific knowledge. The implemented methodology to create the MoDa services and the extension tools consists of six main steps, illustrated in the following diagram.

Figure 1. The methodology



Source: DLR, 2025.

2.1.1. Step 1: Data collection & pre-processing

The raw data sources are stemming from publicly available open-source data, or internally procured data through measurement or data synthesis. Depending on the quality and complexity of the data various data processing techniques are applied to improve the regulation and usability of data.

2.1.2. Step 2: Conceptualization

This step is largely influenced by the formulation of the research question for each of the tools and their specific application. The conceptualization step involves creating a blueprint of the abstract complex problems to be solved for each different aspects of mobility sector, and in particular considering future scenarios, followed by examining and framing their relationship with the energy transition topics. The concepts cover a broad range of issues in the transport sector and are developed in close cooperation with potential users, such as public authorities, industry, and research and development.

2.1.3. Step 3: Modeling

The core of modeling approach relies on computational methods to simulate, analyse, and understand complex mobility and electric mobility systems. State-of-the-art programming languages, such as Python, and its custom libraries are utilized to create representative models of the concepts under investigation. Leveraging modern artificial intelligence techniques such as machine learning and deep neural networks, enable processing of large amount of data to make predictions and produce useful analytics. Such technologies provide the advantage for integration of data and theoretical principles.

2.1.4. Step 4: Scenario generation, simulation and analytics

With the aim of providing insights to the key stakeholders, including government agencies, businesses and the general public, it is quite essential to generate meaningful scenarios for each of the MoDa services. This step delivers customer-oriented scenarios that are relevant and accurate, enabling the MoDa services to reflect the need of various targeted stakeholders. The simulation models provide scientifically-proven analytics that support the mobility and energy stakeholders to plan more efficiently, collaboratively, precisely and cost-effectively.

2.1.5. Step 5: Validation of results & optimization of the model & scenarios

The models within the MobilityLab and within the MoDa-Services were all developed inhouse at DLR. In order to validate the models and the results we went through the typical peer-review process of publishing the results at conferences and in journals. To date 17 publications with the MoDa project (since January 2024) have been published (Bergfeld et al., 2024; Bosch et al., 2025; Grunewald et al., 2025; Hasselwander et al., 2025; Herwartz-Polster et al., 2024; Möring-Martínez et al., 2024; Möring-Martínez et al., 2025).

2.1.6. Step 6: Design and implementation of the user-interface

Having developed the model and data sets, it was then required to create the user interface. This resulted in the creation of the MobiltyLab (see below). This was created by experts in visualization as well as with stakeholders to incorporate their wishes and desires for each module and service. Accounting for these factors, the internal design team within DLR created the MobilityLab, which is constantly being updated with new results and scenarios, as well as feedback from the users and stakeholders.

The following section describes the implementation of the user-interface of the MoDa services and tools in more details.

2.2. The DLR MobilityLab: A MobilityLab for Everyone

As described in the previous section, the DLR MoDa services provide the scientific knowledge foundation that support the DLR tools. Having developed services that are of use to diverse stakeholders, the question then arises how can they interact with these services. The research project DATAMOST merged DLR expertise and innovative research outcomes in an interactive mobility lab for visualization and presentation, referred to as the MobilityLab.

Drawing on DLR's extensive transport sector data, various simulation models are employed within the MobilityLab. These models consider how outcomes such as traffic-related emissions, noise, energy demand, transport demand and accessibility may change as a result of various transport planning measures. New types of transport – autonomous minibuses, for example – can also be modelled, allowing their practical implications to be better investigated.

With the MobilityLab, DLR can model, visualize and evaluate transport measures – even before they are implemented. This allows decision-makers from politics, local authorities and industry to plan more efficiently, collaboratively, precisely and cost-effectively. This lab creates a physical space that allows businesses and society to experience and understand DLR research findings interactively. It promotes the collective, open exploration and evaluation of pioneering mobility solutions by the DLR and its practice partners.

DATAMOST developed the necessary interfaces between cross-disciplinary DLR research findings to shape solutions for mobility transformations. This is achieved by linking existing models, using state-of-the-art data, and employing innovative analytical methods such as machine learning and artificial intelligence. In doing so, the DLR extends transport research through systemic connections and intuitive visualizations. The mobility lab enhances the comprehensibility and visibility of research achievements for society, the economy, politics, and the public.

3. Results

Three main results are produced in this paper: the MobilityLab, the MoDa Services and the tool EPIOT (Electric mobility Prediction Interactive Open-source Tool). Within the Mobility lab there are six modules: Atomsphere/Climate, VMo4Orte, TAPAS/SUMO, CAST, MECO(n), PowerForecastMapper. We go into detail about the PowerForecastMapper. Next, we present the seven MoDa services, and finally, we present the tool EPIOT in detail.

3.1. The MobilityLab User Dashboard – a modular framework for showcasing research models and results

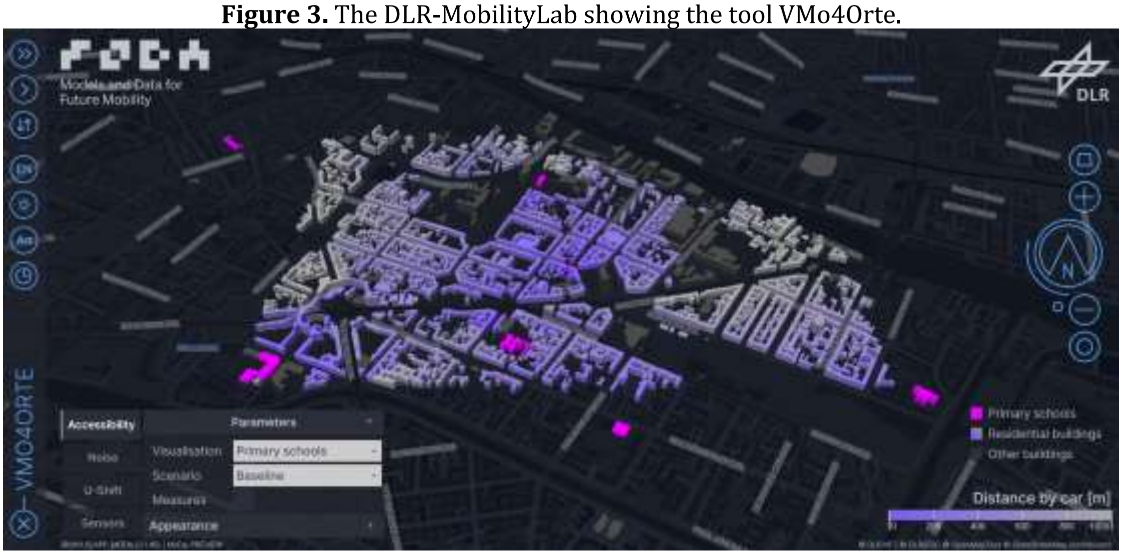
A central aspect of DATAMOST is the methodical expansion of the mobility lab for evaluating mobility solutions. This includes assessing the effectiveness of planned mobility and traffic solutions. The innovative integration of diverse data sources and methods for developing digital twins of mobility solutions and deriving research results at the DLR is noteworthy. Quantitative and qualitative methods for gathering information and developing creative solutions for challenges in the transport system complement each other.

Through its integration, the mobility lab provides added value in evaluation and simultaneously acts as a data provider. It generates data feedback and resulting insights that refine the models used. Furthermore, ensuring transferability to real-world application fields guarantees the market relevance of the mobility lab through targeted and robust results. The DLR MobilityLab is highlighted in the following figures.

Figure 2. The DLR-MobilityLab starting page with different modules on the left-hand side.

Source: DLR, 2025.

Figure 3. The DLR-MobilityLab showing the tool VMo4Orte.



Source: DLR, 2025.

3.1.1. Current modules in MobilityLab

There are currently six modules within the MobilityLab as summarized in the following table.

Table 1. Current list of modules in the DLR MobilityLab

Module	Topic and content
Atmosphere/Climate	*This module presents the results of DLR climate analysis giving results for emissions, pollutant loads, and climate forcing. Scenarios until 2050 are calculated for land-based transportation, international shipping, and aviation.*

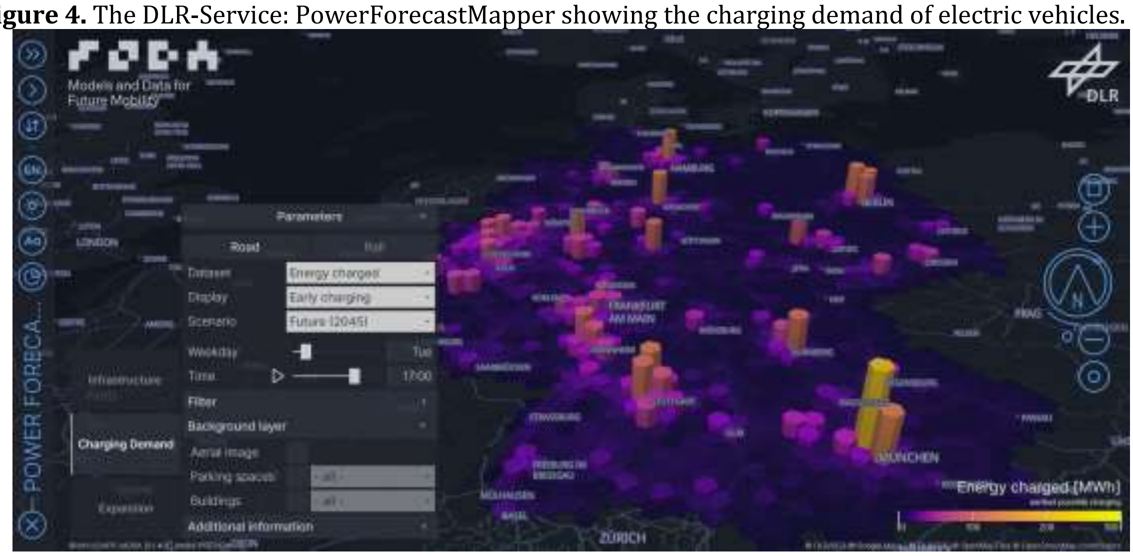
VMo4Orte	*This module illustrates possible mobility solutions within a local Berlin neighborhood. These include autonomous shuttles for passengers and packages as well as traffic calming measures (limiting street access). The results are shown for noise pollution and accessibility.*
TAPAS / SUMO	*This module shows the result for TAPAS (Travel-Activity-Pattern Simulation) and SUMO (Simulation of Urban Mobility) for the case study of Berlin (Heinrichs 2011, DLR 2025a)*
CAST	*This module shows the results from the CAST (Car Stock Mode) for Germany differentiated by federal state. Here new vehicles and technologies are included (with a focus on electric vehicles).*
MECO(n)	*This module shows emissions and pollutant loads with a focus on Europe for non-methane hydrocarbons and NOx for land transport and international shipping.*
PowerForecastMapper (PFM)	*Supports the expansion of charging infrastructure for battery electric vehicles. See below for more detailed insights.*

Source: DLR, 2025.

3.1.2. PowerForecastMapper (PFM)

The expansion of electric mobility requires an efficient and widely available charging infrastructure. This includes not only the siting of charging stations, but also the modification of the power grid. However, this is subject to a high degree of uncertainty, as the demand for charging will increase differently over space and time and grid capacities will have to be adapted accordingly. Along with these challenges, the coupling of the transport and energy systems also offers opportunities such as additional flexibility through time-shifted charging and feeding energy back to the grid.

Figure 4. The DLR-Service: PowerForecastMapper showing the charging demand of electric vehicles.



Source: DLR, 2025.

The service *PowerForecastMapper (PFM)* analyses the charging demands of road-based passenger and freight vehicles as well as local rail passenger transport with high spatial and temporal resolution in various scenarios. Based on the utilization of the existing infrastructure, possible locations and configurations for additional charging points are identified. By examining the interactions with the energy system, the potential for peak load reduction and V2G coupling can be estimated. This service was developed for operators of public and private charging infrastructure real estate and property owners, grid operators, power plant operators, public authorities and policymakers.

Within the DLR research project MoDa we are developing additional services to help stakeholders make decisions about sustainable transportation. These additional services are summarized in the following table along with the new tool EPIOT.

Table 2. Current list of the MoDa services and EPIOT

Module	***Topic and content***
ApplicationSuiteEmissions (ASE)	*Sustainable transformation of mobility – evaluation of climate protection measures in the transport sector.*
MaritimeEmissionsForecaster (MEF)	*Sustainable mobility transformation - identification and evaluation of decarbonization strategies for the maritime sector.*
AirQualityLive (AQL)	*Live particulate matter data in traffic to promote sustainable air quality and mobility.*
TravelExperienceAPI (TEA)	*Development of traveler-centric metrics for evaluating and adaptation mobility services.*
SmartTransitFleetplanner (STF)	*Data-driven simulation and scenario analysis for the integration of autonomous on-demand fleets into public transport.*
TrafficEventFlowcast (TEF)	*Prediction of event traffic through the integration of live data from various sources.*
NewMobilityIndex (NMI)	*A composite quality index of public transport and shared mobility services.*
Electric mobility Prediction Interactive Open-source Tool (EPIOT)	*An electric mobility flexibility prediction tool. See below for more detailed insights.*

Source: DLR, 2025.

3.1.3. Future modules in MobilityLab

A new module, named EPIOT (Electric Mobility Prediction Interactive Open-source Tool), is currently in development and will be integrated into the MobilityLab interactive suite of tools. EPIOT is designed primarily for the quantification of V2G flexibility and optimization of charging station locations in a generic European urban area. Some highlights about the EPIOT module, including the underlying conceptualization and modeling of flexibility, the model architecture and computational methods, data-resourcing and data pre-processing, and finally some selected outputs will be presented in the next section.

3.2. A tool for the management and planning of electric mobility infrastructure

Considering the targets of the EU to promote mass deployment of e-mobility across Europe and implementing V2G along the way, some important research question among the energy scientists has been gaining attention in the recent years. The first question is, how much flexibility can be offered from the e-vehicles in a given urban area, and secondly, how much of this flexibility can be utilized to the benefit of the grid as a V2G application. One may further ask the question; how should we go about expanding the infrastructure and optimizing it to meet the future requirements.

Within the DLR's EU project titled, DriVe2X, a data-driven tool named EPIOT (Electric mobility Prediction Interactive Open-source Tool) is designed and developed with the aim of supporting the Charge Point Operators (CPOs), as well as the Distribution System Operators (DSOs) and smart city planners among others to plan for efficient operation of their system and plan wisely for the infrastructure expansion to accommodate for the rapidly growing number of electric mobility devices in the European future. In this work the aim is to use state-of-the-art computational models to construct a model that can predict the behavior of electric mobility and offer recommendations for an optimized plan for the charging station infrastructure that capitalize on the availability of V2G flexibility.

Figure 5. EPIOT: a data-driven tool for smart city electric mobility management & planning

Source: Own elaboration, 2025

EPIOT is a powerful, interactive energy prediction tool developed to predict the energy profiles (including charging and discharging) of public stations. EPIOT features the methods to predict the charging and discharging flexibility of electric vehicles at a single charging station and additional methods to aggregate at a city level. One of the important features of this tool is to determine the V2G flexibility at the charging station level and use this as the basis for the optimization of the location of charging stations in an urban area (city). EPIOT achieves this by leveraging ML techniques, utilizing a combination of dynamic open-source data gathered and pre-processed from the environment near the charging stations.

EPIOT collects and uses data from publicly available open-source data sources, for example, OpenStreetMap (OSM 2025), therefore, it serves as a generic tool that fits and can work for any city in the EU, with the given basic data. It has the capability to learn from the dynamic data streaming from smart city APIs, for example the charging data from the Charge Point Operator APIs, to predict the day-ahead charging patterns. It is equipped with an interactive user-friendly interface with features that allow for adjusting various scenarios and KPIs to meet the need of diverse stakeholders in management and planning of the electric mobility applications and infrastructure.

3.2.1. Key Performance Indicators

It is crucial to establish KPIs (key performance indicators) and metrics for various stakeholders in the electric vehicle (EV) domain for several reasons. First and foremost, these KPIs and metrics serve as valuable tools for assessing and quantifying the performance and impact of EV-related activities. They enable stakeholders to move beyond raw data and gain meaningful insights, which are essential for informed decision-making in operation and planning. Furthermore, KPIs and metrics provide a common language and framework for communication among different stakeholders in the EV ecosystem. They help bridge the gap between technical data and practical decision-making by translating complex information into clear, actionable insights. This facilitates collaboration and understanding among diverse groups, such as operators, planners, government agencies, and businesses, who all have a vested interest in the success of EV-related initiatives.

However, different KPIs might be interesting for different stakeholders. For instance, a grid operator is more likely to be interested in the loading level of the local transformers because of charging while an environmental committee of the municipality is interested in minimizing the CO2 emissions. By tailoring case studies and utilizing high-quality KPIs, operators and planners can make more effective and efficient decisions. These KPIs guide them in addressing specific challenges and opportunities within their areas of responsibility, ensuring that resources are allocated optimally, and that EV infrastructure is developed in a way that maximizes its benefits for the community and the environment.

There will be five initial KPI categories that will be calculated and tracked, each revolving around different areas such as grid, e-mobility, environment, city, and user. These KPIs can be configured both in terms of spatial and temporal constraints. As an added feature, it is also possible to define and integrate some user- scenarios or aggregated KPIs to investigate the influence of changing city and e-mobility parameters and on the charging stations and the grid.

3.2.1.1. Grid KPI

Building upon the aggregated load profiles of numerous EV chargers and leveraging the grid topology, users are empowered to monitor the load on individual transformers resulting from EV charging. This process is facilitated through the utilization of an open-source Geographic Information System (GIS) grid topology. In essence, an algorithm has been developed to reconstruct the Low Voltage (LV) grid, enabling the tracking of power lines from charging stations to transformers. This approach provides a comprehensive view of the effects of EV charging across different areas within a city.

When users select to focus on a specific transformer, the analytical models, in collaboration with the ML output and the KPI calculator, offer a visual representation of the load profile aggregated at the transformer level. This KPI serves as a valuable tool, especially for grid operators, because it enables them to quantify the impact of EV charging and gain a deeper understanding of the inherent flexibility potential, thereby aiding in more informed grid management and decision-making.

3.2.1.2. City KPI

A useful KPI for urban areas pertains to the occupancy ratio of electric vehicle chargers within a given area. This KPI serves as a valuable resource for city planners, typically associated with municipal bodies, and grid operators in making informed decisions about charger installations. An area with consistently occupied chargers may signal a shortage of available charging points, thus highlighting a potential constraint as the EV population continues to expand in the years to come. In practice, our model capitalizes on the output from the ML model, particularly the details of charging transactions in a day, to visualize the occupancy ratio within areas of interest. For instance, DSOs might be interested in assessing the total chargers linked to a transformer, while municipal authorities might focus on the total chargers within a residential street. This approach empowers both city planners and grid operators to effectively address the growing demand for EV charging infrastructure, ensuring adequate coverage and accessibility for EV users.

3.2.1.3. Environment KPI

The measurement of CO_2 grams saved stands as an environmental KPI that centers around a pressing concern in today's urban landscapes. In detail, the calculation of this KPI is relatively straightforward and directly correlates with the amount of KWh of energy charged within a user-defined area over a specific timeframe. As we transition to a greater reliance on electric vehicles, it not only allows for more efficient utilization of renewable energy resources but also serves to diminish the presence of conventional combustion engine cars on our roadways. Some countries have imposed strict regulations governing carbon dioxide emissions within urban centers. Therefore, quantifying the impact of charging processes is a significant step in the collective effort to safeguard our planet and foster enhanced living conditions in our cities. By reducing CO_2 emissions and promoting cleaner transportation alternatives, we contribute to the betterment of urban environments, making them more habitable and sustainable for present and future generations.

3.2.1.4. User KPI

User KPIs serve as a tool to track the number of charging sessions within a user-defined area during a user-specified timeframe. It allows for a comprehensive understanding of user behavior regarding EV charging. This valuable data enables various EV stakeholders, including CPOs, to assess the potential profitability of establishing charging infrastructure in areas with comparable characteristics. In essence, this KPI contributes to a more informed decision-making process and aids in maximizing the efficiency and effectiveness of EV charging services in response to user demands and preferences.

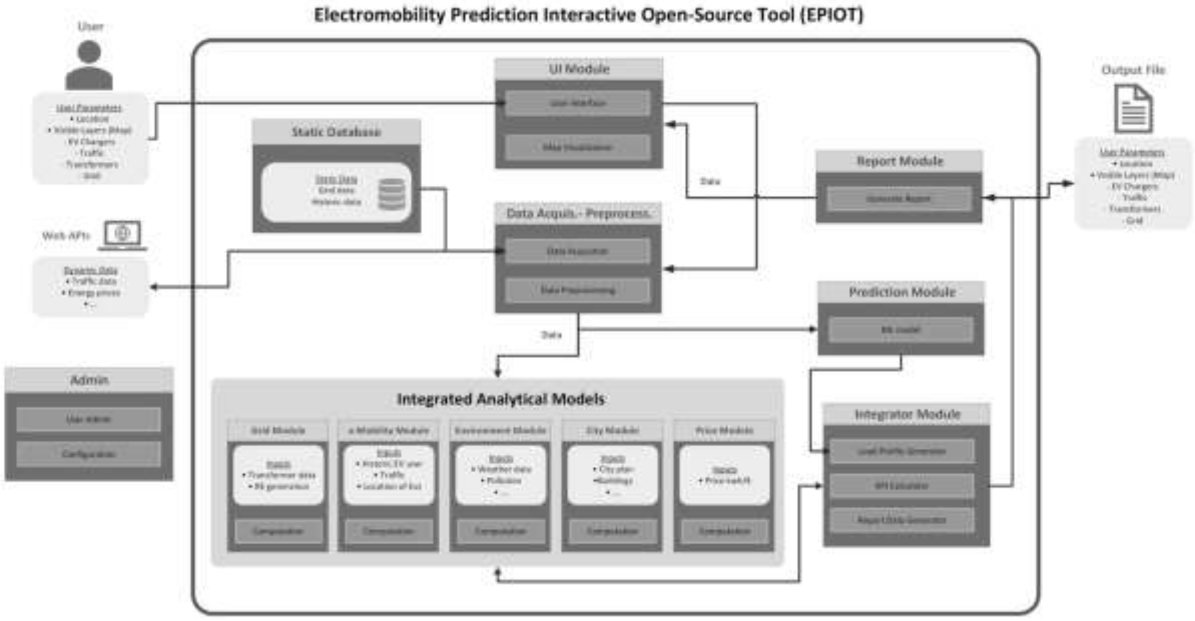
3.2.1.5. E-Mobility KPI

Lastly, we present the metric of drivable kilometers resulting from charging. This e-mobility KPI aligns with the objectives of the KPIs monitoring total energy consumption and the overall number of charging sessions. These metrics collectively offer valuable insights that can guide CPOs and municipal authorities in quantifying the potential for flexibility in smart EV charging solutions. By examining these KPIs, stakeholders gain a clearer picture of how EV charging can enhance e-mobility while optimizing the utilization of the current charging infrastructure.

3.3. Architecture and modules

A version of EPIOT's prototype architecture and its modules are shown in the figure below.

Figure 6. EPIOT Architecture & Modules



Source: Ravanbach et al., 2024.

Starting from the "UI module", this module serves as the main layer of interaction between the user and the data. All the interactive functionalities of the EPIOT can be triggered and viewed on this layer. The main interface features an interactive map where the user can click, browse, and interact to select the type of information to be displayed on the map and the successive windows. This dynamic visualization interface enhances the user's ability to analyze data, offering a comprehensive view of the electric mobility infrastructure and the city parameters in the background. The city elements can be turned on and off (charging stations or transformers, etc.), and more layers including dynamic data from various smart city APIs can be additionality integrated to the map.

The "Data Acquisition module" is responsible for fetching data from a static database or a web API and pre-processing them in the correct format, so that they are usable from other modules. Its main functionality revolves around fetching and pre-processing the data requested by the user through the UI (map), the predictive ML model or the integrated analytical models. All the static information of EPIOT is stored in an open-source, scalable, and reliable database. The "Prediction module" is where the core functionality of the ML module will take place, as introduced earlier.

The "Integrated Analytical modules" will be used for post-processing of ML output to help in the calculation of predefined KPIs. Finally, the "Integrator module" consists of three sub-modules: the load profile generator, the KPI generator and the data aggregator. These sub-modules combine the outputs of the analytical models and the ML module to create a useful final output for the user. Then, the user will have the option to select various parameters in this process, such as which KPIs to compute and their details, the time resolution and the type of data aggregation.

3.3.1. Modeling

3.3.1.1. Definition of flexibility

The objective of this work is to develop a computational model to be used to quantify the amount of V2G flexibility in a generic European urban area in the first step and in the second part to optimize the location of existing charging stations with the objective of maximizing the flexibility exchange with the grid.

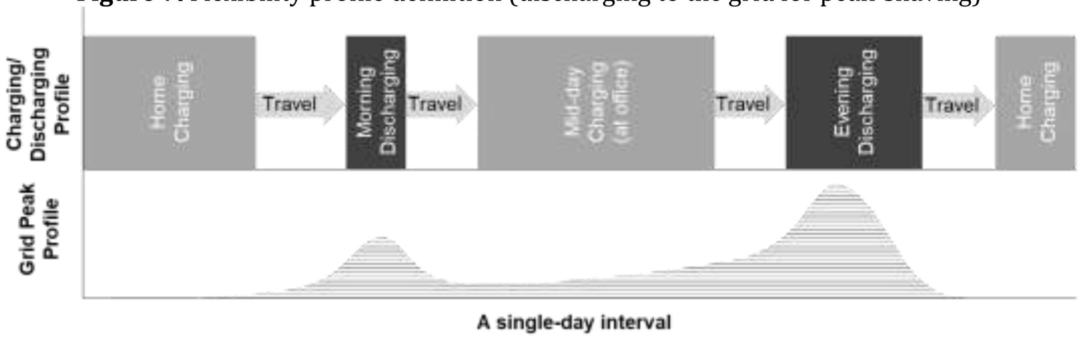
In this work, the flexibility is defined as the electric vehicle's available energy (stored in the on-board battery) to be exchanged with the grid (at the time of charging or discarding) while maintaining the grid requirements (voltage constraints, overloading). Leveraging this flexibility can contribute to supporting the gird, for example, offering peak-shaving, minimizing grid upgrades and absorption of renewable energies.

The modeling of the EV flexibility is undertaken with developing two complementary approaches. One approach is based on machine learning modeling that focuses on the prediction of the charging profile at a single charging station using both temporal and spatial machine learning methods, and the second method based on a rule-based model that investigates the discharging pattern of electric vehicles at the same charging station.

To construct the flexibility profile as defined above, three quantities need to be determined. For a given charging station: 1) how many vehicles are in close proximity over time? 2) how much energy do they offer? And 3) how much discharging is contributed to the gird peak shaving under different scenarios?

Considering the V2G flexibility as a service to the benefit of the grid, for example, peak-shaving, we have modelled the system in such a way to be able simulate the amount of energy discharged at a charging station level to the grid during the peak intervals of the day. In this approach, the model assumes that the charging of electric vehicles takes place only in two locations, at home and at the office, where the EV travels from and to everyday. The discharging can only take place between these two locations and at a public charging station. The graphic below shows the assumption in terms of energy profiles. Light grey boxes illustrate the charging intervals at home or office, and the dark grey boxes indicate the discharging intervals at a public charging station, where the peak shaving can be supported.

Figure 7. Flexibility profile definition (discharging to the grid for peak-shaving)



Source: Own elaboration, 2025

3.3.1.2. System parametrization

Six key interacting elements are determined that together make up the electric mobility system. The selected parameters under each category are listed in the table below (Table 3). The parametrization of the system forms the basis for the collection and pre-processing of data to be utilized in the data-driven machine learning based prediction model. Selecting the right combination of input parameters for each selected element of the system is carried out through an iterative process that is referred to as Feature Engineering. In this process raw variables are transformed into features ready for inclusion in a ML model (Smith, 2017).

Table 3. Description of Electric Mobility System Elements

Category	*Parameter (model input)*

City	City geographical coordinates Number of charging points Charging point's geographical coordinates Building types (office and residential, etc.)
Grid	Charging point's energy monitoring (both present and foreseen) Load demand
Electric Vehicles (EVs)	EV Model Number of EVs EV's energy monitoring (both present and foreseen)
User	EV ownership (owner vs. user) Type (professional vs. private entity) Charging/discharging time per session
Environment	CO_2 emissions
Price	Electricity market price Active dynamic pricing mechanisms

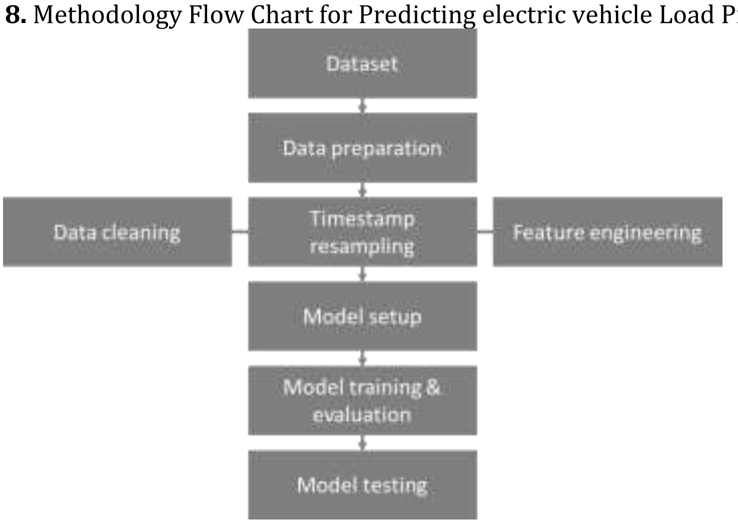
Source: Ravanbach et al., 2024.

3.3.1.3. Application of machine learning methods (an integrated temporal & spatial prediction model)

As mentioned previously a data-driven approach is implemented for the prediction of the flexibility of electric mobility charging infrastructure and the electric vehicle loads at the city level. As an essential component of this approach a machine learning model is implemented that by convention relies entirely on large amount of static and dynamic data as input for learning (training) and subsequently the prediction of flexibility.

The model's output at electric vehicle charging stations shows its predictive capabilities, offering precise insights into the stations' operational status. The following graphic presents a flowchart of the methodology applied in this work.

Figure 8. Methodology Flow Chart for Predicting electric vehicle Load Profiles



Source: Mantri, 2025.

The workflow starts with retrieving the and cleaning the data. Data cleaning involves removing missing values, resolving inconsistencies, and preparing the data in terms of its format and scale for future steps in the analysis. The next step involves resampling of the data to output a consist resolution dataset adjusted to 15-minute or 1-hour intervals (depending on the user setting preferences). In the next step a Feature Engineering method will be carried out, which involves producing new informative temporal and spatial inputs. Some of the newly created features referred to as decomposition elements include, trends and seasonality in the temporal scope and distance to the city center and to some selected city building types in the spatial scope. After improving the model inputs through the feature engineering exercise, a typical splitting of data into training, validation and testing subsets is followed, in preparation for the executing and evaluation of the model (Mantri, 2025).

The model selection (including the setup) is influenced by the objective of the task, prediction of the charging profile at the charging station level, which entails two dimensions: temporal and spatial. From one side, a typical manipulation and prediction of time-series data, in this case, energy profiles, is considered. From the other side, processing of the spatial data collected from the surrounding landscape of the charging stations requires utilization of models that can handle not only the temporal dimension, but the spatial learning (Mantri, 2025). The existing research in the field of electric vehicle demand prediction focuses more on the temporal parameters for electric vehicle charging demand, while ignoring the spatial parameters influencing the charging pattern (He et al., 2022). In our approach location-based parameters influencing the charging pattern such as the distance between the charging stations or distance to nearest parking location are incorporate as part of the learning.

According to Mantri, four suitable models are selected for this task, including:

Persistence: served as a straightforward benchmark

Simple RNN: this model was chosen to explore recurrent neural network capabilities in handling temporal dependencies

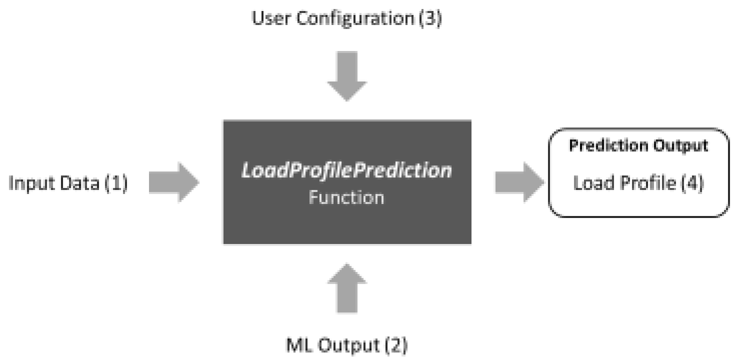
LSTM: known for its effectiveness with sequential data, this model was used to capture longer-term dependencies and variations

GCLSTM: this model was selected to incorporate both temporal and spatial dependencies, which as mentioned before are critical in this application due to the influencing parameters surrounding the geographic location of the charging stations and the inter-relation between the charging stations (the distance playing the main parameter) (Mantri, 2025).

3.3.1.4. The load profile output

The energy profile at a single public charging station is considered as the main output of the envisaged predictive model. The load profile is generated from three data input streams that will be integrated by a post-processing computational function, referred to as the *LoadProfilePrediction* in the figure below. Description of the inputs and the output is described in the following table.

Figure 9. LoadProfilePrediction Function input & output.



Source: Ravanbach et al., 2024.

Table 4. Description of LoadProfilePrediction Module inputs and output

Input Data *(Figure 8, 1)*	The parameters influencing the charging profile at each charging station come from various sources with different forms and resolutions and can be either dynamic or static. The input data include the data acquired from the six key elements of the electric mobility system.
ML Output *(Figure 8, 2)*	The output of the ML model is a data set that predicts the connectivity of electric vehicles at a single charging station for on a day-ahead basis.
User Configuration *(Figure 8, 3)*	The user can configure the spatial scope and temporal scale of data or create custom scenarios

Load Profile *(Figure 8, 4)*	As the output of the predictive model a time-series load profile at a single station is predicted according to the user configuration
Load Profile Prediction function	This module is a deterministic computation function that is responsible for generating the targeted load profile from the inputs explained in the previous rows.

Source: Ravanbach et al., 2024.

The resulting generated load profiles with a relatively high temporal resolution can provide a reliable prediction of the energy balance to the operator of the system on a day-ahead basis. The aggregated load profiles at the city level can provide an overview of the infrastructure performance based on the configured KPIs. The output data can be used by city or grid planners to analyze and optimize the location of the charging stations and the supporting infrastructure on a long-term horizon.

The computation of each charger's load profile doesn't rely solely on the ML output; it is also influenced by user-defined parameters. This is primarily due to the inherent uncertainty introduced by the variable duration of charging sessions. While the ML module excels at predicting charging station occupancy with a high degree of accuracy, it presently lacks the capability to precisely forecast the exact charging behavior of electric vehicles. This limitation is primarily attributed to the scarcity of training data specific to individual charging stations. To address this challenge, we employ user-defined charging strategies to estimate the load profiles of each charging station. One common scenario involves optimizing electric vehicle charging for the fastest possible replenishment, regardless of electricity pricing or grid load constraints. On the other hand, when a charging session extends beyond the duration needed for a full electric vehicle battery charge, the charging behavior can be shifted in time to optimize objectives related to costs or grid stability. Furthermore, our load profile model is further enhanced through the incorporation of statistical data specific to each geographical area. This includes consideration of the characteristics of individual charging stations, such as their rated power and connection type, along with insights into the most common electric vehicle models. Since various combinations of charging stations and electric vehicles possess unique attributes, including battery capacity, minimum and maximum charging rates, they generate diverse load profiles. Therefore, we draw upon statistical distributions that accurately reflect the electric vehicle charging landscape in different areas, ensuring that our estimates are representative of real-world scenarios.

By offering users the flexibility to explore diverse charging strategies and observe their impact on various KPIs, we empower them to tailor case studies that align closely with their unique needs and research objectives. This adaptability enables a more comprehensive and personalized examination of the electric vehicle charging landscape.

3.4. The interactive user-interface and sample analytics outputs

The graphics below show screenshots captured from the online prototype of the EPIOT tool available at: https://drive2x-epiot.ewi.tudelft.nl/. The screenshots show some of the main features and result windows of the tool including:

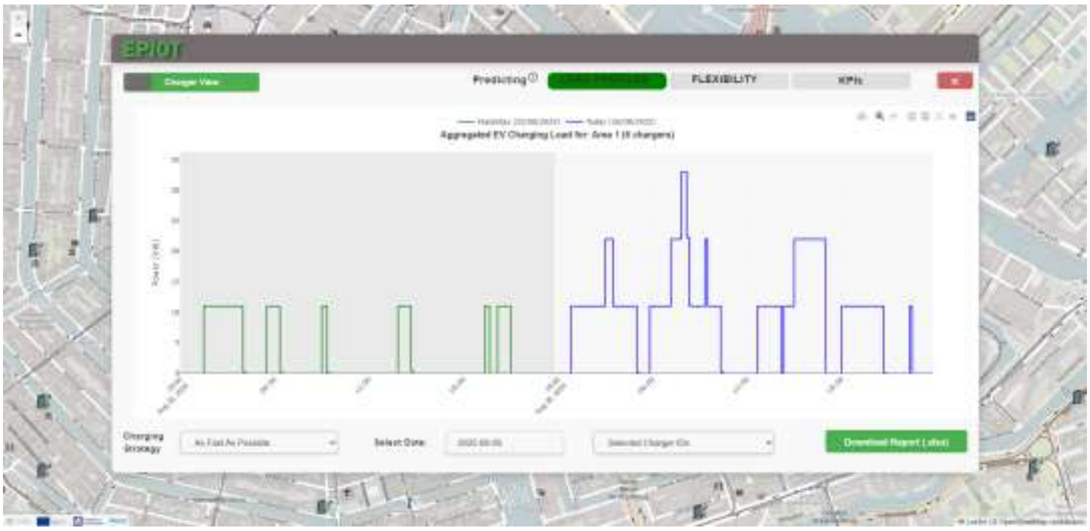
- Landing page: the landing page shows the map of a selected location from the user with charging stations and transformers highlighted with visible icons. The user can select an area of analysis, includes multiple stations and transformers.

Figure 10. EPIOT Landing page (the interactive map of charging stations)

Source: TU Delft, 2025.

- Load profile page: this page will show the predicted load profile for the aggregated or single charging stations selected by the user from the previous landing page. The user can then select a particular charging strategy conveniently by selecting from a drop-down menu at the bottom bar to investigate the influence on the shape of the load profile based on pre-adjusted charging scenarios.

Figure 11. EPIOT Load Profile page



Source: TU Delft, 2025.

- Flexibility page: user can then switch to the flexibility view to view and analyse the discharging pattern of electric vehicles at the selected charging stations (again, both as single and aggregated level).

Figure 12. EPIOT Flexibility page

Source: TU Delft, 2025.

- KPIs page: as the last feature the interface enables the user to browse through some predefined set of KPIs that are generated based on the user selection of area. The user can select a particular station or view aggregated outputs.

Figure 13. EPIOT KPIs page

Source: TU Delft, 2025.

- Report: the user can download a comprehensive report of the analysis anytime by clicking on the green button.

4. Discussion & Conclusion

The successful transition to a sustainable transportation system requires the holistic integration of electric vehicles into the energy system. As such, research projects such as DATAMOST and MoDa play a key role in analyzing complex data and creating models. These models are of most use when stakeholders and policy-makers can directly use them and see the impacts of different measures. Therefore, we created the DLR-MobilityLab to allow such interactive use of numerous models and MoDa-Services. For electric mobility the service PowerForecastMapper and the model EPIOT provide critical insights into the interplay between the transport and energy sectors.

The above study has some limitation though. First, the focus area of the research was limited to Germany and in some cases to Europe. While our goal was always to develop a scientifically sound methodology applicable where ever there is open-source data, the use-case examined are limited to these locations. Secondly, we focus on passenger transport and not mass transit. Thus, the work concentrates on individual vehicles and not larger public transport vehicles (e.g., buses, trains). Finally, the work was completed using open-source data. This limited the analysis of existing electricity grids as this data is not publicly available in Germany. For future research we aim to expand these models to other European countries and create an open-source platform for the DLR-MobilityLab.

EPIOT is a data-driven prototype tool that supports a wide number of electric mobility stakeholders, including charge point operators, distribution system operators and smart city planners of future, enabling them to produce personalised analytics and evaluate different scenarios based on calculated KPIs. Its functionalities and transferable outputs can provide valuable insights on the quantification and optimization of V2G flexibility at the existing or future charging infrastructure in any city in Europe. In essence, such data-driven tools are indispensable for driving the growth and success of the EV industry while minimizing potential drawbacks (Ravanbach et al., 2024).

5. Acknowledgements

The initial development of the DLR-MobilityLab was carried out in the DLR project DATAMOST ("Data and Model-based Solutions for the Transformation of Mobility" (project number 2846048). The work completed within the MoDa project ("Models and data for future mobility_Supporting Services") was funded by the Germany Aerospace Center (DLR) under the funding number 2846141. The initial development of the EPIOT was carried out at the DLR as part of the EU Research and Innovation Project DriVe2X with funding from the European Union (grant number 101056934).

6. Contributions

Ravanbach: Conception and design of the paper, all work regarding EPIOT (concept and design). Anderson: Feedback on design of the paper, all work regarding DATAMOST, MoDa, and the MobilityLab in this paper (entire DLR team responsible for the detailed work in these projects).

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