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***Abstract*—Under new EU regulation, as of 2035 all new cars and vans registered in the EU are set to be zero-emission. This ambitious target will be an important driver for a large-scale rollout of e-mobility across European cities. To ensure the successful planning of the energy infrastructure and optimized operation of the expanding e-mobility systems, smart and robust tools will be in high demand for various stakeholders, such as industry, city planners, or researchers. As part of the EU-funded research and innovation project DriVe2X, an interactive open-source prediction tool for Vehicle-to-Grid (V2G) operation and planning has been conceptualized and is under development. The main functions of this tool are the prediction of energy balance and flexibility at the public charging station level for a day-ahead operation and providing useful customized analytics for long-term planning purposes.**

Keywords—Electromobility, Energy Management, Open-source, Prediction Tool, Vehicle-to-grid

I. Introduction

Under new EU regulation [1], all new cars and vans registered in the EU are set to be zero-emission from 2035 onwards. This ambitious target will be an important driver for a large-scale rollout of e-mobility across European cities. To ensure the successful planning of the energy infrastructure and optimized operation of the expanding e-mobility systems, smart and robust tools will be in high demand for various stakeholders, such as industry, city planners, or researchers.

The energy transition signified by the progress in digitalization of energy and e-mobility sectors will enable automated data flow from a vast number of sensors integrated into the e-mobility system, including both the Electric Vehicles (EVs) and the charging stations. At the same time, advancements in data science will provide the methods to handle and make efficient use of big data. This digitalisation has the potential to lower energy demand and to enhance grid flexibility [2].

As part of the EU funded research and innovation project DriVe2X [3], an interactive open-source prediction tool for e-mobility operation and planning has been conceptualized and is under development. The main functions of this tool are the prediction of energy balance and flexibility at the public charging station level for a day-ahead operation and providing useful customized analytics for the users for long-term planning purposes. The E-mobility Prediction Interactive Open-Source Tool (EPIOT) achieves this by leveraging Machine Learning (ML) techniques, utilizing a combination of dynamic open-source data, and synthetically generated data derived from the local environment surrounding the stations. A selection of charging stations in conjunction with real-world charging data from Amsterdam will be used for the piloting of EPIOT.

EPIOT incorporates a range of integrated analytical models that enable the calculation of Key Performance Indicators (KPIs) tailored to stakeholders' needs. These KPIs are instrumental in assessing the efficiency, performance, and impact of charging stations. EPIOT goes a step further by offering an intuitive, real-time, interactive map visualization of its output, allowing users to customize and explore the parameters that matter most to them.

II. State-of-the-art

With the EU wide transition to e-mobility, the integration of EVs into the grid system presents numerous challenges and opportunities. With the volume of EVs requiring charging there will be a significant increase in demand from the grid. To manage this substantial new load on the grid, several studies have been conducted analysing how best to manage EV charging. Over the last few years, research has shown that ML is a valuable tool in this area. ML can manage very large and complex data sets required for this task, including user behaviour data, charger and EV battery specifications, and charging status and history.

These ML algorithms have been used for optimising charging scheduling and forecasting of the demand. The primary benefits of this are the stabilisation of grid operation and increased grid resilience, but the literature also evaluates its use for modelling revenue and user behaviour.

An analysis of the literature shows that numerous algorithms have been developed for V2G load optimization and EV charging scheduling optimization. Most of these algorithms utilize ML techniques, including Random Forest, Support Vector Machine, Reinforcement Learning, and Long Short-Term Memory networks. The common input parameters used in these algorithms include classification of the charging station (e.g., working place or shopping center), EV battery specifications, charging station specifications (maximum power rating and station type), and information about arrival and departure times of vehicles or the charging duration. A summary of the literature is presented in Table 1.

TABLE 1 – Literature Review

Literature 1	Reference [4]	M.-J. Jang, T. Kim und E. Oh, „Data-Driven Modeling of Vehicle-to-Grid Flexibility in Korea," Sustainability, Bd. 15, p. 7938, 2023.
Objective	Estimation of V2G flexibility with development of a data-driven method	
Application	Modelling the status of EV charging stations for the purpose of estimating their flexibility in V2G	
Model	Queuing theory and mathematical modelling techniques, not a traditional ML method	
Literature 2	Reference [5]	F. Lo Franco, M. Ricco, V. Cirimele, V. Apicella, B. Carambia und G. Grandi, „Electric Vehicle Charging Hub Power Forecasting: A Statistical and Machine Learning Based Approach," Energies, Bd. 16, p. 2076, 2023.
Objective	Development of a method for forecasting the power demand of a charging hub for EVs in different parking scenarios	
Application	Helping in planning and sizing of charging infrastructure for EVs in different locations and scenarios, such as shopping malls, airports, urban car parks, and working places	
Model	supervised machine learning model (no further details)	
Literature 3	Reference [6]	S. Li, C. Gu, J. Li, H. Wang und Q. Yang, „Boosting grid efficiency and resiliency by releasing V2G potentiality through a novel rolling prediction-decision framework and deep-LSTM algorithm," IEEE Systems Journal, Bd. 15, p. 2562–2570, 2020.
Objective	Development of a dynamic V2G scheduling method based on deep-Long Short-Term Memory (LSTM) algorithms and rolling prediction-decision framework	
Application	Prediction and management of the energy capacity of EVs connected to the grid, with the goal of improving the efficiency and resiliency of the power system by implementing dynamic V2G scheduling	
Model	Deep-LSTM algorithm	
Literature 4	Reference [7]	A. Ahmadian, V. Ghodrati und R. Gadh, „Artificial deep neural network enables one-size-fits-all electric vehicle user behavior prediction framework," Applied Energy, Bd. 352, p. 121884, 2023.
Objective	Development of a unified framework for accurately predicting EV user behaviour in terms of charging duration and energy consumption	
Application	Grid management and diverse applications such as consumer behaviour analysis, potential future work of revenue modelling, energy system optimization	
Model	Adaptive learning approach via artificial deep neural networks	
Literature 5	Reference [8]	F. Tuchnitz, N. Ebell, J. Schlund und M. Pruckner, „Development and evaluation of a smart charging strategy for an electric vehicle fleet based on reinforcement learning," Applied Energy, Bd. 285, p. 116382, 2021.
Objective	Demonstration of the effectiveness of reinforcement learning (RL)-based charging coordination in reducing grid load variability and improvement of EV charging efficiency.	
Application	Optimization of EV charging, mitigation of grid stress, and contribution to a more sustainable and cost-effective integration of EVs into the energy ecosystem with an advanced EV charging coordination system for residential areas	
Model	Reinforcement Learning (RL)	
Literature 6	Reference [9]	P. Rajagopalan, J. Thornby und P. Ranganathan, „Short-Term Electric Vehicle Demand Forecasts and Vehicle-to-Grid (V2G) Idle-Time Estimation Using Machine Learning," in 2023 IEEE 13th Annual Computing and Communication Workshop and Conference (CCWC), 2023.
Objective	Improvement of the accuracy of short-term EV charging load forecasts and assess the potential for V2G services by modelling and analysing historical charging data from EV charging stations.	
Application	Improvement on short-term demand forecasting to efficiently allocate resources, and minimization of supply-demand imbalances through the effective utilization of V2G services for more sustainable and resilient energy grids	
Model	Short-Term Demand Forecasting: • SARIMA (Seasonal Autoregressive Integrated Moving Average) • Random Forest • Neural Network (NN) Probability Estimation of V2G Connection: • Logistic Regression • Linear Support Vector Classification (Linear SVC)	
Literature 7	Reference [10]	G. Vishnu, D. Kaliyaperumal, P. B. Pati, A. Karthick, N. Subbanna und A. Ghosh, „Short-Term Forecasting of Electric Vehicle Load Using Time Series, Machine Learning, and Deep Learning Techniques," World Electric Vehicle Journal, Bd. 14, p. 266, 2023.
Objective	Development and comparison of short-term EV demand forecasting models using real-world EV charging data	
Application	Help to grid operators, charging station managers, and EV owners to plan and optimize charging schedules, contribution to a more coordinated and efficient use of resources in the EV charging infrastructure and the overall improvement of reliability and sustainability of EV operations.	
Model	Auto-Regressive and Auto-Regressive Exogenous models Support Vector Regression LSTM neural network model	

These algorithms find application in two main areas: scheduling of EV charging and forecasting of EV charging loads. They optimize the charging schedule of EVs to ensure efficient use of the charging infrastructure, minimize peak loads, and balance energy demand. Some algorithms also predicted future demand for EV charging. These applications can enhance the efficiency of EV chargers, grid stability, as Ahmadian, Ghodrati and Gadh [7] highlighted; these algorithms can be used in the development of revenue models in the EV industry. In our approach, a novel method will be implemented where the learning is based on dynamic acquisition of data from publicly available web Application Programming Interfaces (APIs), and we aim at implementing a transfer learning approach, where the learning from one city can be transferred to another city.

III. Parametrization of the Electromobility System

As a fundamental step toward modeling and analyzing the interaction between EVs and the electricity grid, a parametrization framework is established to obtain an overarching understanding of the key technical elements of the system and its surrounding static and dynamic parameters. One of the objectives of system parametrization is also to create a uniform framework and common approach to collect the relevant set of input for the predictive model across different pilot cities for the project. In this work, we have determined six main interacting elements that together make up the electromobility system as shown in Table 2.

TABLE 2 –Electromobility System Main Elements

Element	Short Description
City	The city contains the charging station(s) and the surrounding urban infrastructure relevant to energy provision and mobility. The city parameters including the roads, buildings or concentration of points of attraction around the charging stations influence the pattern of charging demand and the optimal positioning of them within a city from a planning perspective. In this study we will examine the correlation of city parameters with the charging demand patterns and the optimal location of stations in the city.
Grid	The grid provides the source of energy to the charging stations and absorbs the feed-in energy in the case of bi-directional infrastructure. The topology and capacity of the grid at the point of connection to charging stations will determine the constraints for charging demand and optimal infrastructure planning throughout the city.
EV	The EVs move on the roads carrying the stored energy from one station to another on various time intervals. At the point of connection, they either charge or discharge to the grid. The state of charge (SOC) of the EV battery will determine the charging profile. In this study the EVs batteries will be characterized based on battery size and standard charge and discharge profiles.
User	The user behaviour indicates the time, location and duration of connection of EV to a particular charging station. The user preference for range and charging time influence the profile of the load profile at the charging stations. We aim at generating representative user profiles specific to each demo-site use-case.
Environment	The environment refers to the impact of the EVs on the surrounding environment in terms of both equivalent CO2 saving and reducing pollution in the city.
Price	The price refers to the cost of energy for charging or discharging at the charging station. The price at a charging station provides signals to both the user and the operator that influence the charging behaviour and energy planning respectively.

Our envisaged ML-based predictive model relies on a large set of input data that characterizes the behaviour of the system over time. In technical terms, these variable input data are referred to as input features. Choosing informative and independent features is a critically important part of developing an effective ML model. Selecting the right set of input features for each element of the system involves 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 [11]. Various parameters belonging to each element of the system will be identified and documented, and the complex interaction between them will be explored and analysed. The parametrization of elements will be followed by the identification of sources of data that will be further collected, processed and utilized for the data driven prediction model to be developed in the future tasks.

A. Use-cases & Demo-sites

The public charging stations and the parameters influencing the EV charging profile at each location are considered as the main use-case under investigation. The term "public" refers to the attribute of the charging station that are located on publicly accessible land and continuously available for usage by public EV users (except for certain maintenance or down periods) without any constraints. For example, charging stations that are in a private office parking lot with a gate or attached to an office building with entry codes are not considered as public. The tool is designed to addressed to the following three main use-cases and will be tested and validated in the future for following European cities as indicated in Table 3.

TABLE 3 – Use-cases

No.	Title	Linked demos
1	V2G integration in public charging stations for addressing technical grid constraints	Demo 1 (Isle of Wight, UK), Demo 2 (Maia, PT), Demo 3 (Terni, IT)
2	V2G for network stabilization of locally managed RES-congested grids	Demo 3 (Terni, IT)
3	Peripheral smart renewable energy and mobility hubs for V2G uptake in highly congested urban grids	Demo 4 (Amsterdam, NL)

B. Charging station flexibility profile

The following two research questions emerge by choosing the public charging stations as the main use-case for our study. These two research questions also address the rationale for targeting our prediction output for two different time horizons, the day-ahead and monthly temporal resolution. The day-ahead prediction is intended to meet the demand for day-to-day operations and the longer monthly prediction interval satisfies the requirement for planning the infrastructure. The predicted output is eventually tailored for two distinct types of stakeholders, the charging point operators (CPO) and city and grid planners, accordingly.

The first research question: how much flexibility is available at each existing public charging station in a city over a day-ahead timeframe? And how can this influence the availability and pricing of energy? (short-term prediction, operation).

Stakeholder: The answer to this question or the output of this prediction will mainly benefit the CPOs.

The second research question: how do public charging stations within a city perform with respect to the KPIs? Where would be the optimal location(s) in a city for adding more charging stations or re-arranging the existing installations? (long-term prediction, planning).

Stakeholder: The answer to this question or the output of this prediction will mainly benefit the city and grid planner.

In this context, flexibility is defined as the EVs available battery capacity supplemented to the grid's capacity at the point of coupling while maintaining the grid requirements (voltage constraints, overloading). Leveraging this flexibility can contribute to increasing the use of renewable electricity harnessing unused EV storage capacity, whilst minimizing grid reinforcements and energy generation needs.

To construct the flexibility profile as shown above, three quantities need to be determined:

1. The grid capacity at the point of grid coupling.
2. The grid base load, including residential, commercial, and all other loads, excluding the EVs.
3. The EV load and the unused capacity (amount of the charge in the battery available for the grid to use).

The following series of graphics (Fig. 1, Legend, A, B, and C) aim at illustrating the definition of flexibility in a series of successive graphics that build up the flexibility profile of an exemplary network. In the legend (Fig. 1 _ Legend), the available capacity of the EV is shown in light green, which is the amount of charge in the battery that can be offered or to be discharged to the gird. The dark green depicts the EV charge request from the grid, or the EV load.

In part A (Fig. 1- A) the available capacity of EVs connected to an arbitrary network for an arbitrary moment in time is shown on the left and then supplemented to the grid capacity based on the definition on the right. In part B (Fig 1. B), the available flexibility is expanded for a longer period of daily profile (in this example each column represents an aggregation of 4 hours). In part C (Fig. 1 - C) of the graphic, the flexibility profile of the network is extracted and shown in a separate daily profile.

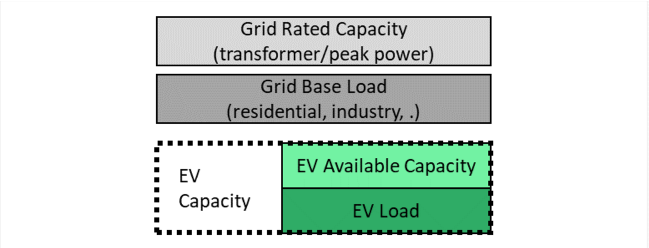

Fig. 1: Legend

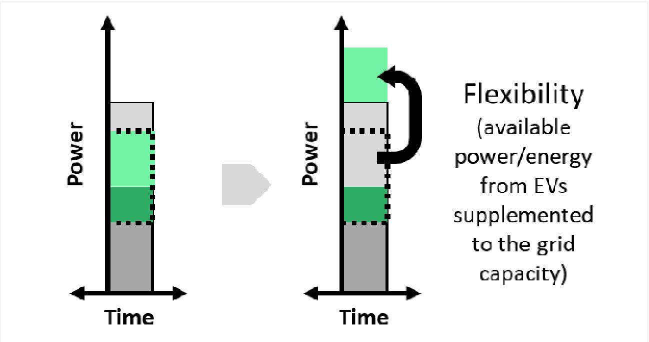

Fig. 1: A

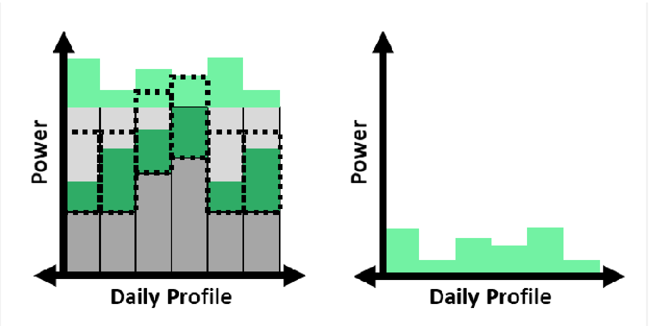

Fig. 1: B (left) and C (right)

The grid capacity is known to us as this value can be obtained from the transformer ratings. The base load will be obtained from locally available standard load profiles. The third variable, EV loads and the remaining unused (available) capacity are unknown; therefore, we are aiming at developing a predictive model to quantify that piece of the argument.

We believe that a day-ahead prediction of the flexibility profile at the charging station level can potentially contribute to the optimization of smart charging strategies in the short term for the flexibility CPOs. The analysis of the aggregated profiles and tracking of the personalized KPIs over a longer period will allow the planners to assess the impact of progressive EV penetration on the grid.

IV. Concept and Architecture of the Tool

EPIOT is an open-source interactive load prediction tool designed to forecast the load profiles of public urban charging stations, both in the short and long term. EPIOT achieves this by leveraging ML techniques, utilizing a combination of dynamic open-source data and synthetically generated data derived from the local environment surrounding the charging stations. Beyond load prediction, EPIOT incorporates a range of integrated analytical models that, with the ML-generated data, enable the calculation of KPIs tailored to various stakeholders' needs. These KPIs are instrumental in assessing the efficiency, performance, and impact of urban charging stations. An early version of EPIOT's architecture is displayed in Fig. 2, where the interaction between various modules is highlighted.

The "UI module" is where all the user-tool interaction functionality will take place. In detail, the user will have the option to interact with a user interface and select what type of information is displayed on the map. This dynamic visualization tool enhances the user's ability to analyze data.

The "Data Acquisition module" retrieves data from a static database and web API, processing it into a usable format for other modules based on user requests from the UI, predictive ML model, or integrated analytical models.

The "Prediction module" is the core of the ML functionality, while the "Integrated Analytical Module" post-process ML output for KPI calculation. The "Integrator module" comprises sub-modules (load profile generator, KPI generator, data aggregator) that combine analytical model and ML module outputs to create a user-friendly final output. Meanwhile, users can customize parameters like KPI computation, details, time resolution, and data aggregation type in this process.

A. *Developmenet & Validation*

The main architecture and components of EPIOT will be developed by the collaboration of DLR Institute of Networked Energy Systems and the Delft University of Technology, where both institutes are dedicating their programming expertise to delivering a state-of-the-art open-source tool. Highlighted as an open-source and modular tool, EPIOT is designed as a research software with straight-forward interfacing and extension capabilities for easy extension by future researchers. Leveraging object-oriented programming in Python ensures code readability and reusability. The Python backend utilizes Flask, while the frontend incorporates powerful JavaScript libraries like Leaflet.js for map visualization and Plotly.js for data representation. During initialization, EPIOT loads all static data required for a session, including properties of charging stations, grid data, and more. To efficiently store this data, a no-SQL database like MongoDB can be employed.

Since the core of EPIOT output is based on machine learning prediction, for the training of the model, validation, and testing of the results, data (both historic and live-data) will be collected and used from the demo-sites mentioned in the previous section A. Use-cases and Demo-sites. The validation and testing will be crucial to ensure the reliability, accuracy, and transferability of the model before its deployment. The challenges involved in this stage are mainly reliability of the dynamic data stream from the demo-site APIs. Methods for risk-mitigation will be put in place, such as storing the data on-a short-time horizon and updating the database frequently.

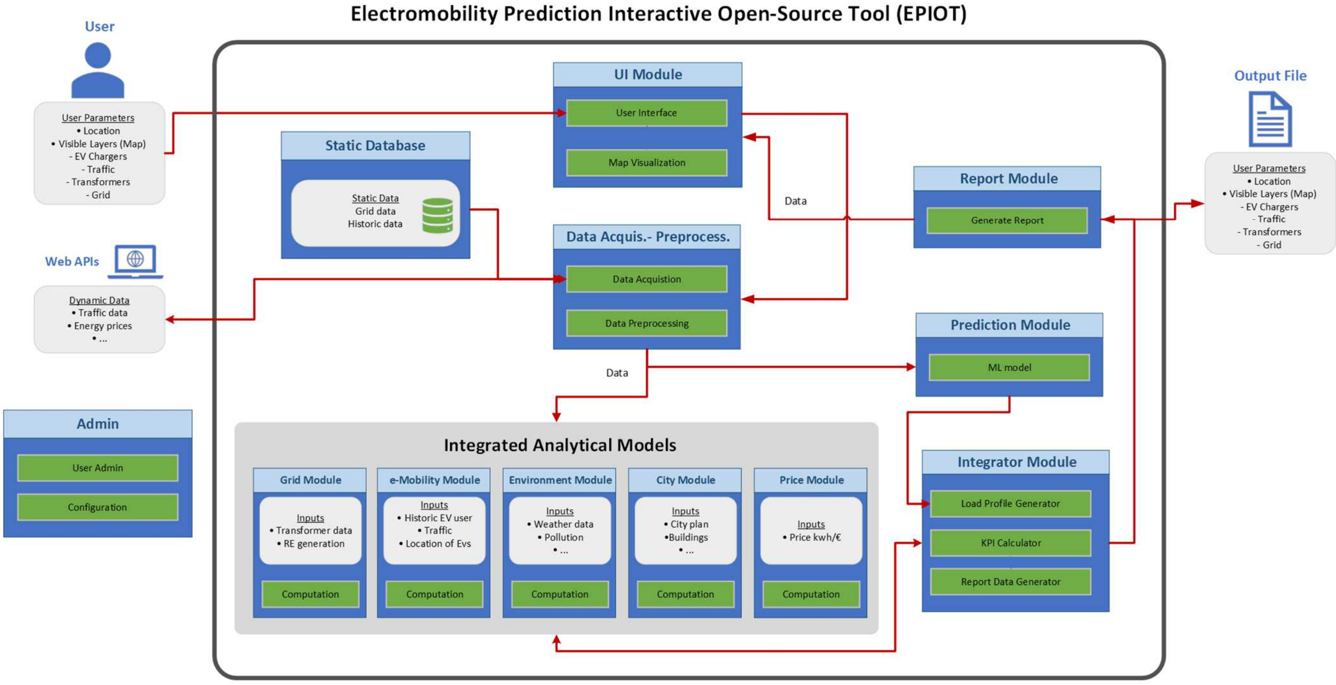

Fig 2. Architecture of EPIOT

B. The Scope

Defining a scalable and transferable scope among demo-site cities is essential. We define the electromobility system as the combination of all the public charging stations and the EVs operating within the geographical boundary of a city. Within this geographical scope, the charging stations act as individual nodes of the system that can provide flexibility by means of exchanging energy between the EVs and the grid (Fig. 3, a). It is further assumed that the geographical scope of each demo-site contains all the parameters that influence the energy exchange at each public charging station. This assumption helps create a common definition among various demo-sites and established a framework for data collection.

We further define another geographical scope on the map for data association and collection, and that is the area of a circle drawn around a charging station with its center pinned to the position of the charging station (Fig. 3, b). The radius of this circle is adjustable to make the coverage area larger or smaller (Fig. 3, c). Fig 2 illustrates this concept for a charging station in Amsterdam.

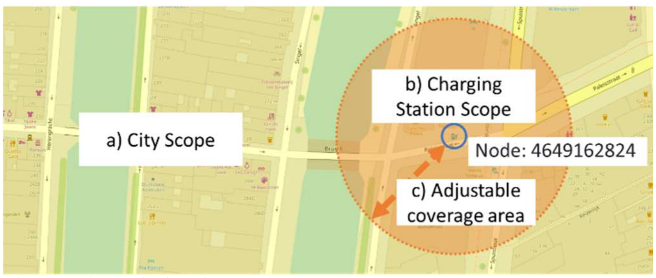

Fig. 3 – City and Charging Station Scope

The highlighted yellow area represents the city scope and the orange circle area with the variable radius centered at the charging station node (#4649162824) covers the charging station data scope. By this definition, there will be two types of geographical scope corresponding to two different areas on the map: the city scope and the other, the charging station scope. For example, the total number of registered EVs in the city is a city parameter (or data), in contrast the traffic density of the adjacent road to the charging station (within the circle) becomes a charging station parameter.

C. Data Sources and Selected Parameters

It is essential to identify and organize the data sources into meaningful sets of information that can be effectively and efficiently used as input for the predictive model. Six high level categories of data sources are defined according to the six elements of the electromobility eco-system, previously defined in this paper. These categories are helpful for guiding the data collection process across the demo-sites and will be also used in the definition of the KPI framework. An important feature of our predictive model is the fact that it will be connected and using many APIs as the source sof input data.

In Table 4, individual selected parameters of the system under each element of the system are listed.

TABLE 4 – Available Data Sources

Element	**Parameters**
City	Charging Station (Location, Rated power, Connector type, Availability)
	Road shapefile & Traffic datapoints
	Point of interest (Location, Schedule, Visitor count)
Grid	System (Generation and Load)
	Transformer and Substation (Location, power, loading)
	RES (rooftop PV Location, installed capacity)
EV	Number of registrations
	Make and model
	Size and category
	Battery size and Charging rate
	Travel range
Environment	Air pollution
	Rain
	Temperature
Price	Day-ahead wholesale electricity price
	EV charging rates

D. Prediction Model

The dynamic ML method of the EPIOT represents a cutting-edge approach that allows for an agile, adaptive system that dynamically absorbs and synthesizes real-time data obtained through open-source APIs. Its core lies in sophisticated algorithms such as recurrent neural networks or long short-term memory models, which process streaming data, allowing seamless integration of updated datasets into the predictive model. This adaptive model continually learns from the city, mobility, user, market and grid parameters and refines its understanding of the complex parameters governing the electromobility landscape.

By employing advanced feature engineering techniques and real-time data ingestion mechanisms, it accurately predicts flexibility potentials. This approach's strength lies in its ability to incorporate live data, ensuring the system's adaptability and efficacy in real-time decision-making.

E. Analytical Modules and KPIs

Establishing KPIs and metrics in the EV domain is essential for evaluating performance and impact, bridging technical data with practical decision-making, and facilitating collaboration among stakeholders. Tailoring KPIs to specific stakeholder interests, such as grid operators' focus on transformer loading levels and environmental committees' emphasis on CO2 emissions reduction, enables more effective decision-making. High-quality KPIs guide operators and planners in addressing challenges and opportunities, optimizing resource allocation, and maximizing the benefits of EV infrastructure for communities and the environment.

To address this need, we've designed five integrated analytical models that play a key role in facilitating the post-processing of the ML prediction output and the data sourced from static databases or accessible web APIs (Fig. 2) These models are necessary in the evaluation of the KPIs at hand. The workflow begins with the user, who plays a central role in shaping the analysis. The user initiates the process by specifying essential parameters, such as the preferred time resolution (day-ahead or month-ahead) and selecting the region of interest based on administrative areas, postal codes, or neighborhoods, through a visual interface. In the end, the outcomes are presented on the user's screen, accompanied by the option to generate a downloadable report for later analysis. This approach empowers the user to wield control over the analytical process, allowing them to tailor the analysis to their unique areas of interest and research objectives.

F. Results & Output

As previously highlighted, EPIOT features a customizable interactive visual user interface, empowering users to tailor their analyses by selecting from available KPIs and their parameters, as well as defining the geographical scope of their analysis. Fig. 4 illustrates a screenshot of the initial version of EPIOT. As depicted, users can designate the chargers they wish to study within a specified administrative area. Moreover, users have the flexibility to choose which KPIs to calculate through the wizard located in the left-side panel. In this example, we demonstrate the day-ahead predicted load profiles for the selected charging stations. It's worth noting that this represents the first iteration of EPIOT, with ongoing development and enhancements planned.

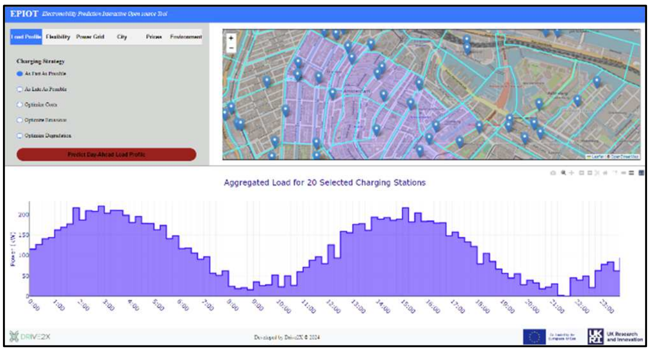

Fig. 4 – Screenshot of the EPIOT UI.

Conclusion

In summary, EPIOT is a versatile tool that caters to a wide array of electromobility stakeholders, empowering them to create custom case studies and evaluate KPIs using real, readily available data. Its capability to provide real-time insights and predictions makes it an invaluable resource in the rapidly evolving field of electromobility. Its functionalities and outputs support the aforementioned stakeholders on determination, quantification, prediction and optimization of V2G flexibility at existing or future charging stations.

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