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eMob-Twin: A Digital Twin for Electromobility Flexibility Forecast [★]

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Abstract: As environmental concerns grow, Electric Vehicles (EVs) are becoming essential for sustainable urban traffic. Some countries plan to phase out conventional vehicles to cut carbon emissions. Yet, challenges include a lack of charging infrastructure and potential strain on power networks. EVs could benefit by integrating Vehicle-to-Grid connections. To leverage e-flexibility, modeling EV power requirements and mobility patterns is crucial. The paper presents eMob-Twin, a digital twin, combining urban EV mobility with an energy model, aiding simulations with fine granularity including charging stations, its potential connections with the Grid and electricity markets. We present details of the structure and operation of eMob-Twin and some examples of their utility in connection with user cases such as impact of the EVs penetration rate, and optimal locations of charge stations.

Keywords: Electromobility, Digital-Twins, Mobility, EVs, Simulation tools.

1. INTRODUCTION

Although the power sector is managing to quickly reduce its carbon footprint, the transport sector is lagging far behind the pledges made by all the countries represented at successive IPCC COPs. In 2023, barely 18 % of the 77 million light-duty vehicles sold worldwide were fully electric vehicles (EVs in short). By 2030, however, EVs will account for 70% of all the vehicles sold, according to the EU roadmap (the Fit for 55 plan), which envisions a ban on the sale of new petrol and diesel cars as early as 2035. Contrary to what is generally thought to be the case, electromobility (e-mobility), i.e., the electrification of the transport system, will not necessarily be a hurdle to the development of future electric power systems, where most synchronous generators will be replaced by utility-scale and behind-the-meter renewable energy sources (RES). Massive amounts of daily and seasonal storage capacity will be required in the medium-term future in order to properly compensate for the lack of RES dispatchability.

On the daily horizon, a large portion of this storage capacity could be provided by EVs (here named *e-flexibility*), if the future vehicle-to-grid (V2G) technology is duly developed and managed to meet the needs of the moment. The electrification of transport could therefore help to integrate much larger amounts of renewables at a lower cost, which is crucial to achieving Europe's long-awaited energy independence. One of the main potential barriers to fully exploit the *e-flexibility* potential available (by optimizing the infrastructure, and developing new EV services and business strategies), is the lack of tools and methods for forecasting EV fleets' *e-flexibility* in both time and space, in terms of hours and kilometers. This means being able to

forecast when and where EVs are going to move, how their State of Charge (SoC) is evolving, and how they going to interact with the infrastructure and the power grid.

2. GOALS AND FUNCTIONALITIES

eMob-Twin results for leveraging the results of the *ERC-AdG Scale-FreeBack* Canudas-de-Wit (2017-23), resulting in e-mobility simulation tool driven by digital twin technology. It is tailored for the Grenoble metropolitan area, but a new version under development, will be able to capture any other metropolitan city in France, and will include auto-calibration features as well. It addresses maily EVs mobility and tehir state of charge, but also includes multi-power charging stations. Companies, stakeholders, and electricity markets can use eMob-Twin for various purposes such as forecasting, analysis, and unlocking EV flexibility. Examples of such potential uses are:

- Predicting the density and state of charge (SoC) of electric vehicles in a specific area for the upcoming week. Users of eMob-Twin can adjust the penetration rate of EVs, allowing them to assess whether the existing public charging stations are sufficient in both quantity and power to meet the overall energy charging demands of the EVs..
- Predicting energy demands for electric vehicles in a specific area enables Transmission System Operators (TSO) to identify potential hot spots where energy congestion is likely to occur in the power grid,
- Optimal placement and power-capacity dimension of charging stations. eMob-Twin users may be able to set the number of charging stations required, and the interface will help to compute their optimal locations and power-capacity,
- Determining the ideal locations and power capacity for charging stations. Users of eMob-Twin can specify the desired number of charging stations, and

[★] Funds from PoC eMob-Twin 2023-24, and from the ERC-AdG Scale-Free Control for Complex Physical Network Systems. Scale-FreeBack, Canudas-de-Wit (2017-23)

the interface will assist in calculating their optimal placement and power capacity.

- Evaluation of charging strategies for ride-hailing fleet operators. Operators will be able to compare the cost of charging and profit from being able to serve the transportation demand using various strategies, etc.

3. MATHEMATICS MODELS

The EV flexibility model in eMob-Twin is based on the results from ERC AdG Scale-FreeBack, which provides a large-scale mobility model describing daily movements in an urban network. This model generates a dynamic bipartite graph representing origins and destinations, utilizing an origin/destination matrix with connection directions, weights, and temporal profiles. Nonlinear ordinary differential equations (ODEs) describe aggregated anonymized movements, including EV mobility with battery charging/discharging dynamics (State-of-Charge or SoC).

The model incorporates charging station models of varying power levels with states including the number of EVs at each node ($N_i(t)$), EV flow between nodes $\phi_{i,j}(t)$ [veh/h], normalized average SoC of EVs at each node $\varepsilon_i(t) \in [0, 1]$, and total energy in EVs at a node $E_i(t)$.

In what follows we provide a description of the general functionalities of the model shown by the block diagram in Fig. 1. For a more detailed description, refer to Rodriguez-Vega et al. (2023).

3.1 People mobility module

To model the people's mobility we use the model introduced in Niazi et al. (2021), and extended and applied to the Grenoble urban metropolitan area in Pratap et al. (2022), which is based on a set of coupled conservation Ordinary Differential Equations (ODEs) of the form

$$\dot{N}_i^h(t) = \sum_j (\phi_{j,i}^h(t) - \phi_{i,j}^h(t)) \quad (1)$$

where N_i^h corresponds to the number of people in node i , and $\phi_{i,j}^h$ is the flow of people from node i to node j .

3.2 Fastest-path graph module

This module generates a graph, denoted as G , wherein each pairing of origin node i and destination node j specifies the path topology (in the $x-y$ coordinates). These paths are designed to minimize the free-flow traveling time for vehicles moving between nodes i and j . Subsequently, the path topology information is utilized in the charging station module to identify the public chargers utilized by electric vehicles (EVs) along the path. Moreover, the module calculates various metrics for each path, including the length $\ell_{i,j}$, the average vehicle speed $v_{i,j}$, and the average road inclination $\theta_{i,j}$.

3.3 Mode choice module

To shift from conventional mobility to electric vehicle (EV) mobility, it is essential to initially determine the proportion of individuals utilizing private cars. This task, known as modal choice analysis, has been extensively

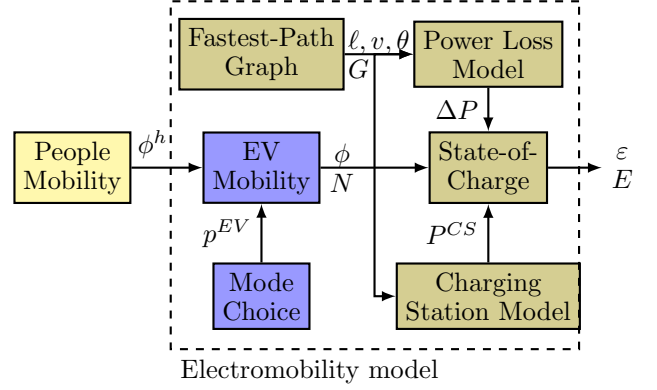


Fig. 1. The Electromobility Model consists of seven modules: people mobility, mode choice, EVs mobility, fastest-path graph, power losses, charging station model, and State-of-Charge. These modules collectively compute node populations, flow between nodes, EV numbers, EV flow, paths for EVs, power losses during trips, power injection at charging stations, and aggregated State-of-Charge and energy of EVs at each node. Figure taken from Rodriguez-Vega et al. (2023)

explored in existing literature, as referenced in Bouscasse et al. (2019); Mondal and Bhat (2022). In this context, we employ the well-established logit model, which assesses the likelihood that an individual opts for their private vehicle over public transport, in terms of the probability $p^{car}(\Delta t)$, depending on the traveling time difference between public transport and private cars, Δt .

3.4 EVs mobility module

Once the number of cars performing each trip is known, the corresponding number of EVs, N_i , can be computed using the penetration rate η from the mass conservation property,

$$\dot{N}_i(t) = \sum_j (\phi_{j,i}(t) - \phi_{i,j}(t)) \quad (2)$$

where

$$\phi_{i,j}(t) = \eta p^{car}(\Delta t_{i,j}) \phi_{i,j}^h(t). \quad (3)$$

3.5 Power loss module

The total power lost during the EVs displacement from node i to j is described by:

$$\Delta P_{i,j} = \phi_{i,j} E_{i,j}^l \quad (4)$$

where $E_{i,j}^l$ is the average energy lost per vehicle Fiori et al. (2016),

$$E_{i,j}^l = E^F(\ell_{i,j}, v_{i,j}, \theta_{i,j}) + E^v(v_{i,j}) + E^{aux}(\ell_{i,j}, v_{i,j}) \quad (5)$$

where the first term, E^F , represents the losses due to external forces from $i \mapsto j$, The second term, E^v , is the kinetic energy needed to reach a speed v without consideration of energy losses, and the last term, E^{aux} , is the energy used by auxiliary vehicle systems (e.g. air conditioning).

3.6 Charging station module

To model the power injected by charging stations, we consider three types of chargers: a) Home Chargers (HC), b) Office Chargers (OC), and c) Public Chargers (PC).

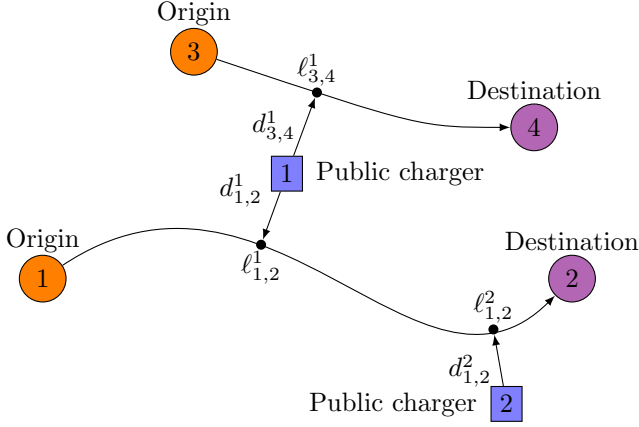


Fig. 2. Example with 2 OD paths and 2 PC from Rodriguez-Vega et al. (2023). The arrows from the PC to the path indicate if the PC supplies power to EVs making this trip according to the “attraction” between the PC and the path. $\delta_{i,j}^k$ is the distance between PC k and the path (i, j) , and $\ell_{i,j}^k$ is the distance from i to k along the path towards j .

Home chargers These chargers are only present at origin nodes (residential) and their injected power, P_i^{HC} , is modeled as the product of the the average power per charger, P_{HC}^{avg} , times the number of EVs at home during the night that are willing to charge when their power is below a given threshold (i.e. $\min(N_i, N_i^{HC})$).

Office chargers These chargers are available at destination nodes at workplaces and shopping areas. The supply power from OC, P_j^{OC} , follows similar model as HC, with P_{OC}^{avg} being the average charger power, and N_j^{OC} is the number or chargers at location j .

Public access chargers The charging stations, known as PC (Public Chargers), serve vehicles in transit between nodes. The specific location and average power per station in the area are provided. Since PC locations are not necessarily directly aligned with a specific Origin-Destination (OD) link but are situated in their vicinity, it becomes necessary to define how these charging stations contribute to supplying power to each link in the graph.

To address this, we initially determine which PC will furnish power to each link in the graph using a gravity attraction law, as outlined in Barbosa et al. (2018). This law takes into account the shortest distance between the geographic location of the PC and the link’s graph on one hand, and the average power supply capacity of each station on the other. The underlying rationale for this model is that drivers are more likely to be “attracted” to nearby PC locations with ample power availability. This attraction “force” of station k to the link (i, j) , is denoted as $A_{i,j}^k$, and depends on: the average power charging station capacity, P_k^{avg} , the distance between node i and the closest point to PC k along the path (i, j) , and the distance that people are willing to deviate from their original destination path to go for a charge. We consider that a given PC k is connected to (i, j) if the normalized attraction law is larger than a given threshold.

Once the CS is declared to be connected to a given link, the power provided by this station to the identified link is

computed by using a demand/supply rule, of the form

$$P_{i,j}^k = \min(D_{i,j}^k, S_{i,j}^k) \quad (6)$$

where the demand D specifies the maximum power that the flow of vehicles in the route can receive, and the supply S specifies how much power can be provided by the PC. If it is connected to multiple routes, the maximum power is divided proportionally according to the energy needs of each route,

Power in each node from all chargers contributions For each origin node i , the total received power from charging is the sum of the contributions from home chargers and public chargers located in the D/O paths,

$$P_i^{CS}(t) = P_i^{HC}(t) + \sum_j \sum_{k \in \Omega_{(j,i)}} P_{j,i}^k(t) \quad (7)$$

and for each destination node j the total received power from charging is the sum of the contributions from office chargers and public chargers located in the O/D paths,

$$P_j^{CS}(t) = P_j^{OC}(t) + \sum_i \sum_{k \in \Omega_{(i,j)}} P_{i,j}^k(t). \quad (8)$$

3.7 State-of-Charge module

The dynamics of the energy stored by EVs in node i is given by an energy-balance law

$$\dot{E}_i(t) = P_i^{CS}(t) + \sum_j (P_{j,i}^{in}(t) - P_{i,j}^{out}(t)) \quad (9)$$

where $P_{j,i}^{in}$ is the power flow entering node i from j , $P_{i,j}^{out}$ is the power flow exiting node i towards j . The energy in each node is given in terms of the SoC:

$$E_i(t) = CN_i(t)\varepsilon_i(t) \quad (10)$$

and the power transported out by EVs is

$$P_{i,j}^{out}(t) = C\phi_{i,j}(t)\varepsilon_i(t). \quad (11)$$

The power entering each node takes into account the link losses

$$P_{i,j}^{in} = P_{i,j}^{out} - \Delta P_{i,j}. \quad (12)$$

Note that from (10),

$$\dot{E}_i = C(\dot{N}_i\varepsilon_i + N_i\dot{\varepsilon}_i). \quad (13)$$

Substitution of (2), (4), (11), (12), and (13) into (9) and rearranging terms gives

$$\dot{\varepsilon}_i = \frac{1}{N_i} \left(\frac{P_i^{CS}}{C} + \sum_j \left(\phi_{j,i}(\varepsilon_j - \varepsilon_i) - \frac{\Delta P_{j,i}}{C} \right) \right). \quad (14)$$

4. MODEL PARAMETER CALIBRATION

The model is calibrated for the Grenoble metropolitan area in the French Alps, whose boundaries are shown in Fig. 3. Highlighted in orange are the 60 origin nodes representing the municipalities. Highlighted in purple are the 374 destination nodes. The population in the area is approximately 470.000 people. Calibration is performed using data sources and algorithms exclusively from public government agencies and open source repositories, see Table 1 in Appendix 7

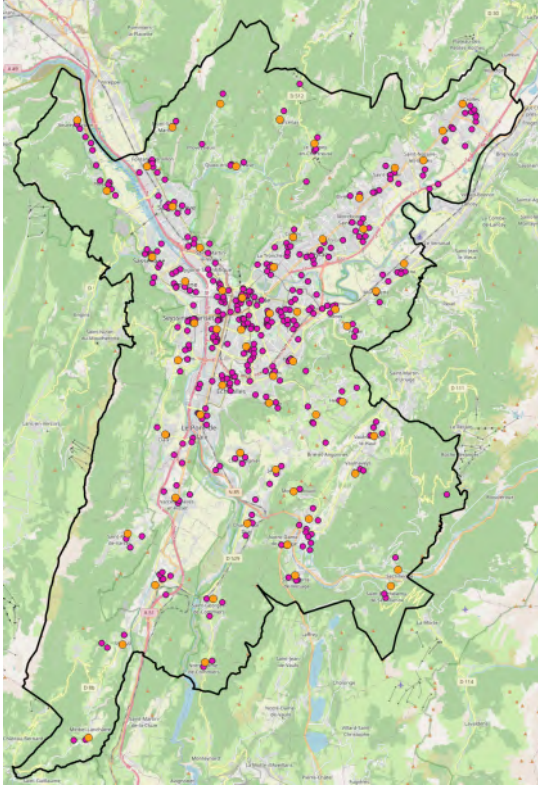


Fig. 3. Layout of the Grenoble metropolitan area. Orange circles represent origin nodes; purple circles are destination nodes.

4.1 Human mobility calibration

The calibration process for the people mobility module is extensively explained in Pratap et al. (2022), relying solely on open data. While we omit specific details regarding this portion of the model calibration here, we provide a more in-depth description below, focusing on the calibration process of the others modules of the electric vehicles models components.

4.2 EVs mobility calibration

Paths attributes. To compute the road-paths between origin and destination nodes, we compute the road network graph using the fastest-path algorithm OSMnx with input data from OpenStreetMaps. The paths are given as a set of point coordinates, and the lengths and traveling times between consecutive points are also provided by the algorithm. Node elevations were obtained from MERIT-DEM. We used the road network graph and the fastest-path algorithm implemented in OSMnx using the free-flow traveling time.

Mode choice parameters are computed from the household survey EMD2010. This dataset provides the number of people using car or public transport according to: the origin and destination sectors, and destination class. While the EMD2010 sectors do not precisely align with the nodes in the electromobility model, calibrated parameters from EMD2010 will be applied to the electromobility model as both consider the same population. For sample n in EMD2010, p_n^{car} represents the proportion of surveyed individuals using cars for an OD pair and destination class.

The average travel time difference Δt_n is computed using OSMnx for cars and OpenTripPlanner for public transport

Number of EVs by municipality The current distribution of EVs number and penetration rate by municipality can be seen in Fig. 10, obtained from the Ministry of Ecological Transition. The city of Grenoble, however, has a lower penetration rate, as it contains a larger vehicle population. The northeast axis, although having fewer total vehicles, have a similar number of EVs, as evidenced by a higher penetration rate. It can be seen that some areas in the north have very high penetration rates compared to the rest of the map. However, these areas have very few vehicles in total, so the high penetration values might be artificially high.

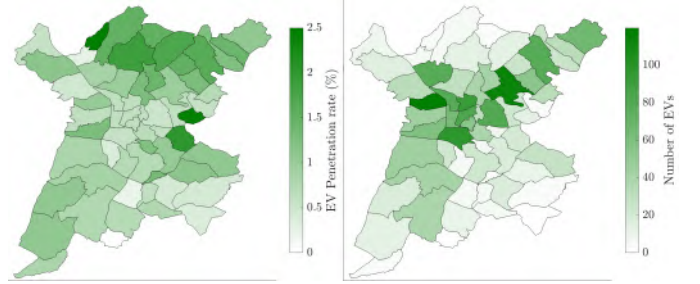


Fig. 4. Spatial distribution of the penetration rate, and numbers of EVs by municipality (2023).

Charge stations data. The locations of the *Public chargers* are obtained from OpenChargeMap. To determine which PC contributes to each link, we use the process described in Section 3.6 with the paths computed using OSMnx. To estimate the number of *Home Chargers* in each municipality, we use parking data from EMD2010, which provides the proportion of vehicles parked overnight in private garages, shared parking, or roadside spaces. We assume that EVs with access to a private garage also have access to a home charger. Therefore, we calculate the number of home chargers by multiplying the proportion of vehicles parked in garages by the total number of registered EVs in municipality. Finally, The average power per home charger is obtained from ENEDIS. Estimation of the number of *Office chargers* and its related power is done by using the data provided by ENEDIS, which specifies the ratio between the number of PC and the number OC at a national level. As the number of PC in the area is known, the total number of OC is calculated proportionally. For each destination node, the number of OC is distributed in proportion to the node capacity.

5. SOFTWARE DESCRIPTION

This section describes the software from two distinct perspectives: the user interface and the software technical architecture.

5.1 User interface

The eMob-Twin software interface has two main components: a map centered on Grenoble metropolis showing various geographical data, and the simulation parameter selection and graph display.

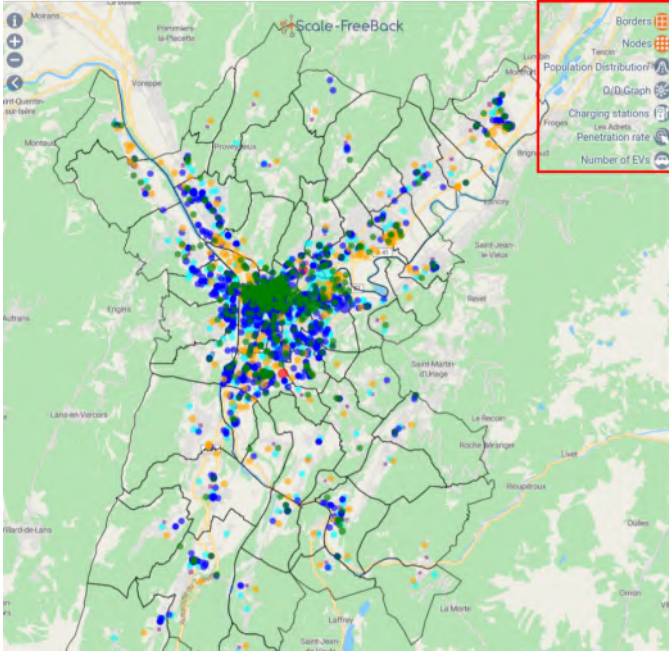


Fig. 5. EMob-Twin map of Grenoble area, with the layer selection buttons highlighted in red.

The map component of the interface is inherently linked to a series of layer selection buttons (shown in the red square in the Fig. 5). These buttons allow the user to choose which static data he wishes to display. Available layers/buttons are:

- **Borders:** Displays division borders, with divisions consisting of all communes in the Grenoble metropolitan area.
- **Nodes:** Shows locations of O/D nodes, with their types and capacities. Destination nodes are organized per categories (schools, hospitals, workplaces, shopping centers, and leisure spots). Users can select node types and choose to display all nodes or only aggregated nodes that will ultimately be used by the model. You can see these aggregated nodes on Fig. 3.
- **Population Distribution:** Presents a heatmap depicting population density across the Grenoble region.
- **O/D Graph:** Illustrates the Origin/Destination people mobility matrix, showcasing links between origin and destinations nodes and their respective daily mean flow, with link importance indicated by a color gradient, as shown on Fig. 6.
- **Charging Stations:** Displays the location and type of charging stations, including public and private stations at work and home, with tooltips providing additional station-specific data (CSO, power per chargers, etc.). The different type of CS are displayed in Fig. 7.
- **Penetration Rate:** Presents a choropleth map indicating the EVs penetration rate in each commune, with color gradients representing rates from 0% to 5%.
- **Number of EVs:** Shows the absolute number of electric vehicles in each commune.

A large tab (at the left in Fig. 8) enables users to define input parameters for simulations from a preset list. Main parameters include average penetration rate [0-100%], simulation duration in weeks, initial state of charge [0-

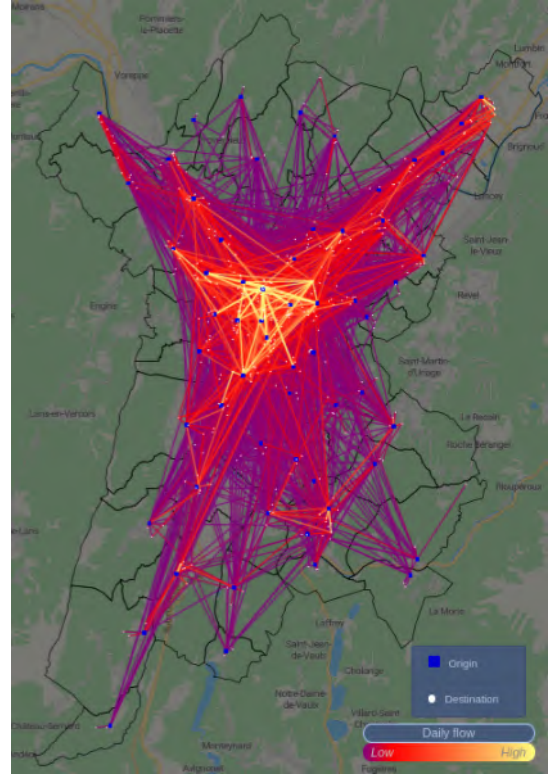


Fig. 6. EMob-Twin O/D network as shown in the interface

100%], and public charging station occupancy, crucial for testing various scenarios. Additional parameters include multiplicative factors on charger numbers and average charger power at home and work, allowing for further scenario exploration.

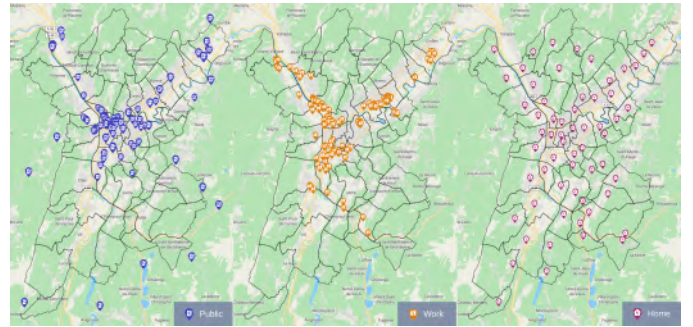


Fig. 7. EMob-Twin platform visualization of charging stations locations around the Grenoble area

Upon completion of the simulation, the interface displays model outputs through a few data visualizations. Four plots depict this simulation output data, with time in days as the x-axis. (Fig. 9)

Visualizations include:

- **State-of-Charge (SoC) of EVs:** Sum of energy in Wh over time or mean SoC $\in [0, 1]$ of all EVs.
- **Power Provided by Charging Stations:** Total power provided at each time in W or total cumulative energy provided in Wh.

A red vertical bar, moving along the x-axis, indicates the current time for geographic data visualizations. In the same manner, users can interact with a timerange to

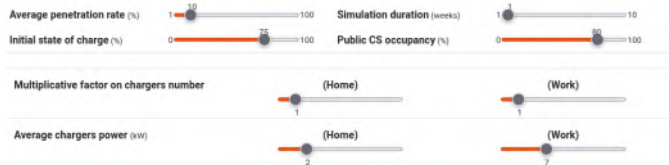


Fig. 8. EMOB-Twin parameters selection for simulation

animate time-dependent data visualization on the map. Indeed, the most significant data visualization occurs directly on the Grenoble map. It includes:

- **Energy Distribution heatmap:** Shows energy distribution of energy stored in all EV batteries
- **Energy distribution choropleth:** Show energy distribution aggregated by division
- **Mean State of Charge choropleth:** Displays mean state of charge of EVs aggregated by division

These visualizations provide comprehensive insights into model outputs and facilitate scenario exploration and analysis.

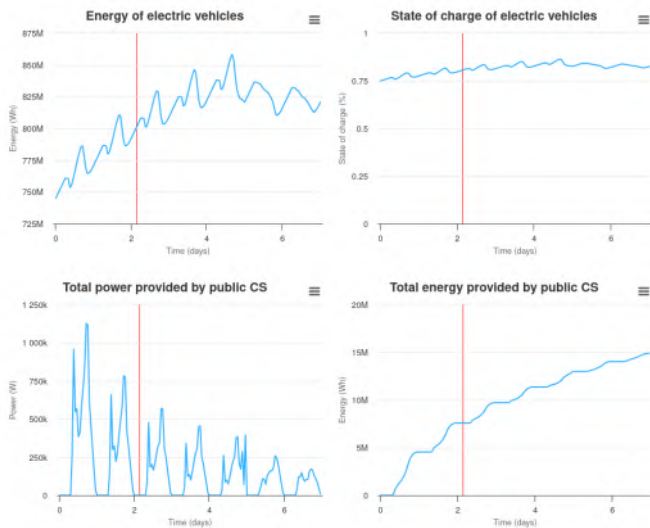


Fig. 9. EMOB-Twin simulation results as shown in the interface

5.2 Software architecture

The model relies heavily on actual static data for parameter calibration, sourced from various open data repositories accessible online, primarily governmental platforms and local organizations. This data encompasses global mobility patterns and electric vehicle-specific metrics such as EV distribution per region and detailed information on public charging stations. The diversity of data sources is illustrated in Tab. 1, necessitating an initial preprocessing step as part of our data mining process.

Once cleaned, the data for the Grenoble area is statically stored in optimal solutions tailored to each data type, including geographic, time-sensitive, and statistical data, primarily in static files of various formats (geojson, json, csv, etc.). This static source of truth serves as a readily accessible foundation for our model.

The model itself is implemented as a Python library, leveraging both Python and C, designed for ease of use and

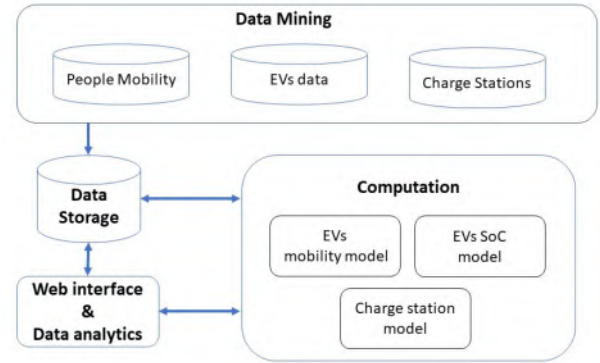


Fig. 10. EMOB-Twin technical components

extensively documented. Its internal structure comprises three model layers housing the seven submodules outlined in Fig. 1, intricately interconnected to compute the model output.

- The EVs mobility layer utilizes the people mobility and mode choice modules to determine the number of EVs at each node and the flow of vehicles along links over time.
- The charging stations layer utilizes EV mobility data, alongside details of public and private charging stations and user behavior, to forecast EV charging demand over time.
- The EV state-of-charge layer leverages the outputs of the previous layers, combined with road network topology, to calculate the final state of charge for vehicles across all links and nodes throughout the day.

For the eMob software, which is computationally intensive, the model runs on a backend server. A task queue, built using Celery - a distributed task queue framework - and Redis — an in-memory data structure store serving as a message broker — manages tasks efficiently.

Communication between the task queue and the front end of the software is facilitated by Flask, a Python web framework. Flask handles incoming web requests from users, such as launching simulations with specified parameters, by managing the model in the task queue, executing simulations, collecting results, and responding to user requests with simulation outcomes for display. Due to the duration of simulations, which can last several tens of seconds, simulations are run asynchronously, with the front end making periodic requests to track simulation progress and retrieve final outputs upon completion.

The front end of the interface, also served by the Flask server, is constructed using HTML and CSS for static components and JavaScript for interactive features. Geographic information and maps are displayed using the Leaflet library, which dynamically retrieves OpenStreetMap (OSM) data.

6. USER CASES AND EXAMPLES

6.1 Sustainability

In the context of electric vehicles, sustainability refers to the ability to develop and maintain a charging infrastructure that meets the increasing demand for electric vehicle

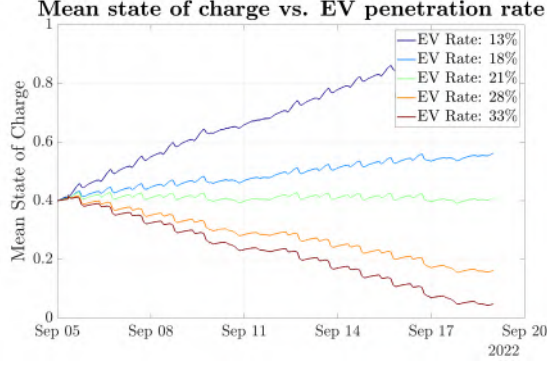


Fig. 11. Evolution of the mean state of charge with varying EV changing penetration rates, from Rodriguez-Vega et al. (2023)

charging. using eMob-Twin, we can examine the sustainability existing charging station network in Grenoble. The goal is to identify the critical electric vehicles penetration rate, denoted as η^* , at which the charging station network becomes incapable of satisfying the energy requirements of EVs, indicating a phase transition. For that, we define the overall average SoC of all EVs in the network as

$$\bar{\varepsilon}(t) = \frac{\sum_i N_i(t)\varepsilon_i(t)}{\sum_i N_i(t)}. \quad (15)$$

Fig. 11 shows the trajectories of $\bar{\varepsilon}(t)$ from an initial condition $\bar{\varepsilon}(0) = 0.4$, where each color corresponds to a different η . We note three cases: *a*) for $\eta < 0.22$, $\bar{\varepsilon}$ increases and then remains around a value close to 1; *b*) for $\eta > 0.22$, $\bar{\varepsilon}(t)$ decreases until vehicles are discharged; and *c*) for $\eta = 0.22$, $\bar{\varepsilon}(t)$ oscillates around the initial value. Thus, there exists a phase-transition value $\eta^* = 0.22$ that differentiates between sustainable charging and discharging of vehicles.

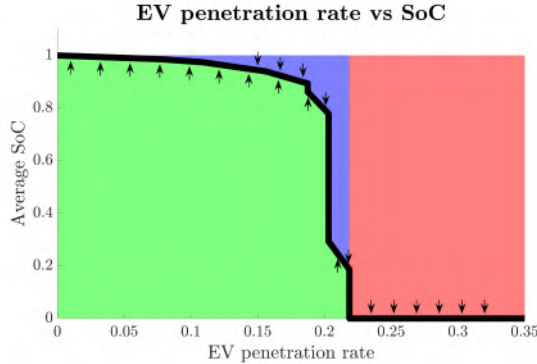


Fig. 12. Behavior of the average SoC trajectories according to the penetration rate and initial conditions. The black line is an attractive invariant set, as all points move vertically toward the line. Points in the red region will move towards 0. From Rodriguez-Vega et al. (2023)

Figure 12 displays the phase portrait of $\bar{\varepsilon}(t)$ versus η . The plot is segmented into distinct regions based on trajectory behavior. The black band indicate an attractive invariant set; initial conditions outside this band converge toward it. Arrows indicate trajectory directions for trajectories reaching the invariant set. Three main sub-regions are identified: green sub-region describes the sustainability domain; red region the unsustainable one, and the blue region is the transition one.

6.2 Optimal CS placement

The optimal placement problems can be formulated as follows. First, complete electromobility model is be compactly written as

$$\dot{N} = \mathcal{I}\phi(t), \quad (16)$$

$$\dot{\varepsilon} = f(N(t), \phi(t), \varepsilon(t), u) = f(t, \varepsilon, u), \quad (17)$$

where u here represent the vector of the CS locations to be optimized. The dynamic of $\bar{\varepsilon}(t)$ can be approximated using the Taylor expansion of f around $(\bar{N}, \bar{\phi}, \bar{\varepsilon})$ as

$$\dot{\bar{\varepsilon}}(t) \approx f(\bar{N}, \bar{\phi}, \bar{\varepsilon}(t), u). \quad (18)$$

where $\bar{N}, \bar{\phi}, \bar{\varepsilon}$, are week averaged variables of N, ϕ, ε , respectively: $\bar{N} = \frac{1}{T} \int_{t-T}^t N(\tau) d\tau$, $\bar{\phi} = \frac{1}{T} \int_{t-T}^t \phi(\tau) d\tau$, $\dot{\bar{\varepsilon}}(t) = \frac{1}{T} \int_{t-T}^t f(N, \phi, \varepsilon, u) d\tau$.

The optimal CS placement problem is then formulated as finding the solution of the above optimizatoin problem

$$\begin{aligned} \min_{u \in \mathcal{U}} J(\bar{\varepsilon}^*, u) \\ \text{s.t. } f(\bar{N}, \bar{\phi}, \bar{\varepsilon}^*, u) = 0, \end{aligned} \quad (19)$$

where $J(\varepsilon, u)$ is the cost function considering profits for the charge stations operators, user satisfaction, and social equity,

$$J(\varepsilon, u) = \underbrace{J_1(\varepsilon, u)}_{\text{profit}} + \underbrace{J_2(\varepsilon, u)}_{\text{satisfaction}} + \underbrace{J_3(u)}_{\text{equity}}, \quad (20)$$

Information regarding this formulation, along with initial findings featuring academic examples, is available in Mourgues et al. (2023). Our current research activity aims at extending this approach to cover the entire Grenoble area and identifying optimization solutions to facilitate scalability. The resulting algorithms will be integrated into a forthcoming version as part of the eMob-Twin V1 update.

7. FURTHER DEVELOPMENTS

Further advancements in the eMob-Twin platform are currently focused on two main objectives:

The first objective involves enhancing the platform's applicability to any major urban area in France. By maintaining the utilization of open data sources, efforts are directed towards expanding local datasets to national databases. We are then able to use geographic filtering for specific regions, enabling the computation of tailored calibration parameters and granting users the capability to utilize the platform for their desired area.

The second objective entails a redesign of the user interface to enhance the user experience and enable practical application of the model. For instance, integrating access to our optimal CS placement algorithm within the platform would serve as a valuable tool for local authorities to develop their strategies of CS development or validate their approaches against our findings.

8. CONCLUSIONS

In conclusion, as global environmental concerns escalate, Electric Vehicles (EVs) play a crucial role in achieving sustainable urban traffic. However, challenges persist, including a lack of charging infrastructure and potential strain on

Source	Function	Data
National institute of statistics	Calibration of people mobility	Node population and capacity
Mobility and Urbanism agencies of Grenoble-Alpes region	Calibration of mode choice model, and number of HC per node.	Household mobility survey EMD2010: inter municipality trips, and type of parking used.
OpenStreetMaps, OSMnx	Computation of car trajectories and traveling time.	Car road graphs and fastest-path calculation algorithms.
SMobility agency of Grenoble-Alpes region	Computation of public transport traveling times.	Public transport map and itineraries.
OpenTripPlanner	Computation of public transport traveling times	Fastest path algorithm.
MERIT-DEM: Open source data	Road inclination computation for energy loss.	Digital Elevation Map
ENEDIS: French energy distribution system operator.	Calibrate the number and power of chargers.	Number of chargers of each type at the national level and total power.
OpenChargeMap	Input data for PC.	PC location and nominal power.
Ministry of Ecological Transition	Initial condition for EVs distribution	Number of vehicles, EVs and penetration rate per municipality.

Table 1. Data sources description for parameter calibration.

power networks. To overcome these obstacles, integrating Vehicle-to-Grid (V2G) connections becomes imperative for optimizing EV efficiency. This paper has presented eMob-Twin, a digital twin merging urban EV mobility with an energy model, facilitating simulations with fine granularity. eMob-Twin’s structure and operation offer valuable insights, demonstrated through examples like assessing the impact of EV penetration rates and identifying optimal charge station locations. The tool proves instrumental in addressing challenges and optimizing EV integration into urban environments. Digital twins, like eMob-Twin, significantly contribute to advancing sustainable urban mobility and managing Electric Vehicle ecosystems effectively. More advanced versions of eMob-Twin are under developments to include grid connections, and interactions with electricity markets.

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