Impact of mass-scale deployment of electric vehicles and benefits of smart charging across all European countries

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Abstract

The mass-scale integration of electric vehicles into the power system is a key pillar of the European energy transition agenda. Yet, the extent to which such integration would represent a burden for the power system of each member country is still an unanswered question. This is mainly due to a lack of accurate and context-specific representations of aggregate mobility and charging patterns for large electric vehicle fleets. Here, we develop and validate against empirical data an open-source model that simulates such patterns at high (1-min) temporal resolution, based on easy-to-gather, openly accessible data. We hence apply the model - which we name RAMP-mobility - to 28 European countries, showing for the first time the existence of marked differences in mobility and charging patterns across those, due to a combination of weather and socio-economic factors. We hence quantify the impact that fully-electric car fleets would have on the demand to be met by each country's power system: an uncontrolled deployment of electric vehicles would increase peak demand in the range 35-51%, whilst a plausible share of adoption of smart charging strategies could limit the increase to 30-41%. On the contrary, plausible technology (battery density) and infrastructure (charging power) developments would not provide substantial benefits. Efforts for electric vehicles integration should hence primarily focus on mechanisms to support smart vehicle-to-grid interaction. The approach is applicable generally beyond Europe and can provide policy makers with quantitatively reliable insights about electric vehicles impact on the power system.

1 Introduction

In the framework of the European Green Deal, the European Union aims at reducing its greenhouse gas (GHG) emissions by 55% by 2030 and at achieving carbon neutrality by 2050 [1]. To reach such goals, decarbonisation policies need to increasingly target multiple energy end uses beyond power generation, such as transport, heating and industrial process. Transport, in particular, is at the core of European decarbonisation policies, with a pledge to curb emissions by 90% by 2050. In fact, transport alone accounts for about a quarter of all EU GHG emissions, second only to power generation [2].

Of all transport emissions, more than 43% are associated with passenger light-duty vehicles [3], which also represent the most utilised passenger transport mode, accounting for up to 73% of the total passenger-kilometres travelled in the European Union in 2018 [2]. The substitution of conventional light-duty vehicles with equivalent electric vehicles, to be powered by renewable electricity, is hence one of the pillars of the European transport decarbonisation strategy. In fact, in addition to entailing lower life-cycle emissions compared to conventional vehicles [4, 5], electric vehicles are expected to bring about a number of additional benefits. They can improve the energy self-sufficiency of households [6] and they can provide key flexibility for the power system, thanks to the implementation of smart charging strategies that make possible the bi-directional exchange of energy between vehicle batteries and the electricity grid as a function of renewable generation patterns [7, 8, 9].

Yet, the integration of electric vehicles into electricity grids may be difficult to achieve in practice. Regardless of the degree of implementation of smart charging strategies, a mass-scale penetration of electric vehicles would entail a substantial increase in the demand of electricity compared to what power systems are currently designed to meet [10], and the extent to which generation capacity would need to be expanded to cope with such new load is still an unanswered question. Furthermore, there is a trade-off between the provision of flexibility to the power system through frequent charging and discharging events and the need to mitigate the vehicle battery degradation associated with those [11], which, if not carefully optimised, may affect the appeal of vehicle-to-grid contracts from a user perspective [12]. To address such questions and allow a frictionless integration of large electric vehicle fleets into the power system, an accurate and context-specific representation of their aggregate mobility patterns and charging behaviour is critical. For instance, stakeholders still have conflicting views around the impact of electric vehicles' load on the current electricity demand and if and to what extent this could be mitigated by smart charging behaviour, or by an adaptation of power systems operation to such load [13]. Providing quantitative insights around such open issues through accurate modelling could support the resolution of such conflicts and the implementation of appropriate policies.

The main challenge to this end lies in reproducing mobility patterns and charging strategies despite a limited availability of data. In fact, with a few exceptions, such as Germany [14], detailed mobility data are missing for most European countries. This leads to a wide range of approaches to reconstruct random user behaviour. A common strategy relies on Markov chains, which require highly precise and resolved data for their calibration [15], and are therefore hardly applicable Europe-wide. Alternative approaches have been so far applied only in combination with electric vehicle field trial data, which are still rare and context-specific due to electric vehicles being still in an early adoption phase (the share of electric vehicle sales has reached the 3.5% in 2019, while their share in the total vehicle stock is still no more than 1% [16, 17, 18]). For these reasons, as further discussed in the following section, previous work has either managed to model accurate mobility and charging profiles only for single, data-rich countries, or managed to estimate Europe-wide profiles at the expense of adapting context-specific profiles to the whole continent.

With this work:

1. We develop an open-source model that simulates electric vehicle mobility and charging time series at high (1-min) temporal resolution solely based – the first of its kind – on easy-to-gather, openly accessible data. The model grounds on the previously developed RAMP engine [19] for stochastic user behaviour simulation, expanding it with mobility-specific features. The model also includes the

possibility to simulate multiple plausible charging strategies and to account for the effects of different weather years.

2. We validate the model against real-life charging transactions metered in the Netherlands, demonstrating good accuracy across a range of metrics.

3. By applying the model to 28 European countries, we identify and discuss time-explicit differences in electric mobility demand across those, accounting for both weather- and user-driven diversity.

4. We analyse the impact that electric vehicle demand would have on the current electricity demand profile and the extent to which alternative 'smart-charging' strategies and technological or infrastructural developments could mitigate electric vehicle demand peaks, again accounting for differences in boundary conditions - such as renewable generation patterns - across contexts.

The model, which takes the name of 'RAMP-mobility', is released under an open-source license for transparency and reproducibility purposes [20]. It is freely accessible on GitHub [21], as well as permanently archived on Zenodo alongside the data required to generate results for all Europe [22].

2 State of the art of mobility and charging time series modelling

State-of-the-art approaches for simulating mobility and charging time series commonly ground on stochastic modelling methods that allow reproducing the random aspects of user behaviour. They can be grouped for simplicity into: i) approaches based on Markov chains; and ii) approaches based on other stochastic methods.

Markov chain approaches simulate user behaviour as a series of subsequent 'states', for which moving from a starting state to a given destination state is associated with a specific probability. Fischer *et al.* [15] modelled electric vehicle charging profiles at 1-minute resolution and their impact on residential electricity load demand by means of an inhomogeneous Markov chain process, which differentiates user behaviour depending on the travel departure and arrival location: inside town, outside town, home and workplace. Such differentiation, made possible by the abundance of data (70'000 surveyed car trips) made available by German institutions [14], limits on the other hand the model relevance to the German context alone. Similarly, Muratori [23] proposed an heterogeneous Markov chain model to simulate behavioural patterns related to the uncoordinated charging of electric vehicles with a 10-minute resolution. To generate activity patterns, they calibrate the model on highly-detailed household habits data for the US, including a wide range of activities (e.g. cooking) beyond mobility itself. As a limitation, such-built activity patterns are hardly applicable seamlessly beyond the US as well as hard to substitute with equivalent data more broadly across contexts. Iversen *et al.* [24] adopted a so-called hidden Markov model, considering only two user states (driving and non-driving), calibrated on data gathered from a field trial to simulate charging profiles at 1-minute resolution. The field trial was limited, however, to a single vehicle for a period of 183 days, again hindering a wider model applicability. Furthermore, they model only two charging strategies, one uncontrolled and one 'vehicle-to-grid' based on an exogenous power exchange limitation. An inhomogeneous cyclic Markov chain process is proposed also by Gruosso and Gajani [25]. They model charging profiles at 15-min resolution calibrating user activity patterns on field data from 800 electric vehicles used in Italy for a car sharing project, which yet strongly limits the possibility to adapt the model to different contexts and to the mobility patterns of privately-owned cars. What is more, charging profiles are obtained by the simple application of a standard, pre-defined charging cycle to the previously computed mobility patterns, preventing the simulation of different plausible charging strategies. A more peculiar case is that of the model proposed by Gaete-Morales *et al.* [26]. Despite not explicitly referring to Markov-chain theory, they use a sampling approach for the generation of 15-minute-resolved mobility demand time series that grounds on the definition of chains of events, again relying on data provided by German institutions [14]. The model distinguishes between commuters and non-commuters and between alternative travel purposes and destinations, each linked to different charging infrastructure availability probabilities and charging power capacities. It includes the possibility to customise some assumptions, such as the charging strategy, and is released open-source. Yet, the extremely data-rich characterisation of user behaviour, recalling that of Markov-chain models, hinders the model re-parametrisation and adaptation to contexts for which only coarser data - for instance, with no explicit mention of 'where' users are in each moment, which prevents the mapping of chain-of-event probabilities - are available. A similar sampling approach, grounding on the same highly-detailed data source for Germany, is proposed by Wulff *et al.* [27] to synthesise user mobility patterns. Out of such mobility patterns, they produce hourly charging profiles, including both uncontrolled and smart strategies, through a multinomial logit utility function that accounts for charging location and electricity price. Yet, in addition to the limitation of a heavy-intertwining with German data, the model does not account for seasonal mobility behaviour changes nor for holidays.

Other stochastic methods, instead, generally aim at reproducing the randomness of user behaviour without assuming a consequential relationship between subsequent events. At the expense of losing real-life details about how certain user activities might influence subsequent ones, these approaches potentially have the advantage of requiring substantially less resolved input data. For instance, Schäuble *et al.* [28] developed a stochastic process that randomly varies for each user the number of connections in a day, the power charging curve, the charging start time, and the initial state of charge of the vehicle battery, without an explicit modelling of user chains of activities. By such method, they modelled both uncontrolled and smart time series with a 1-minute resolution; however, they relied exclusively on field trials data, hindering adaptability to more broadly available data sets. Harris and Webber [29] proposed a Monte Carlo method that allows to randomise parameters such as trip starting time and trip duration for different categories of users, combining easy-to-gather data, such as national time-of-use surveys, with field trial data related to charging behaviour. They applied it to the simulation of 1-minute-resolved uncontrolled charging profiles. Similarly, Brady and O'Mahony [30] developed a Monte Carlo approach to simulate mobility and charging patterns, grounding on the data collected from a 15-vehicle field trial over 9 months. As the aforementioned ones, the model shows the potential for a simple stochastic approach to the modelling of mobility patterns compared to Markov chains, yet has the strong limitation of grounding on a non-generally-applicable type of data set. Furthermore, the model only works over a 2-week simulation period, and does not allow capturing seasonal effects.

Overall, Markov chain and similar data-heavy approaches emerge as a viable option whereas highly resolved and abundant mobility data are available, so as to explicitly characterise users chain of activities over a day. However, they are hardly applicable to large-scale modelling across different European countries, which is key in the framework of the European Green Deal. In addition, the heavy intertwining of the simulation algorithm with present-day user behaviour data required by Markov chains hinders the applicability to long-term mobility patterns and to extreme sensitivity scenarios which substantially deviate from present-day boundary conditions. Conversely, other stochastic processes are preferable whereas only simple data, such as time-of-use surveys, are available. The reliance on simpler and smaller sets of parameters also makes such approaches more flexibly adaptable to different contexts and suitable for the simulation of long-term or extreme scenarios. Yet, all generic stochastic approaches proposed so far failed to decouple their algorithms from context-specific field trial data regarding charging behaviours: rather than first developing generally-applicable stochastic approaches and then testing their validity against particular field-trial data, previous studies went in the opposite direction, over-fitting models to specific field trials and missing out on adaptability to all European countries.

There is a need for a generally-applicable stochastic approach that capitalises on the already existing, Europe-wide accessible data about the daily activities and type of vehicles of different population groups to model mobility patterns, and which then allows for the simulation of *multiple* plausible charging strategies (including both smart and conventional ones), based on widely applicable literature data and on the modellers needs and assumptions. What is more, the approach should account for demand changes over the year due to both changes in user behaviour (e.g. holidays) and temperatures effects on battery consumption, in such a way to ensure a functional coupling with power system models across weather years. The methods that we present in the Methods section and implement in RAMP-mobility precisely aim at fulfilling these needs for the first time.

3 Methods

Our modelling approach (summarised in Fig 1) is composed of two subsequent simulation modules: i) the mobility module; ii) and the charging module. The mobility module is meant to generate minute-resolved mobility patterns for each user, whilst the charging module uses the previously generated mobility time series to compute the corresponding charging load demand, which also depends on the stochastic availability of charging points and on the charging logic adopted by each user.

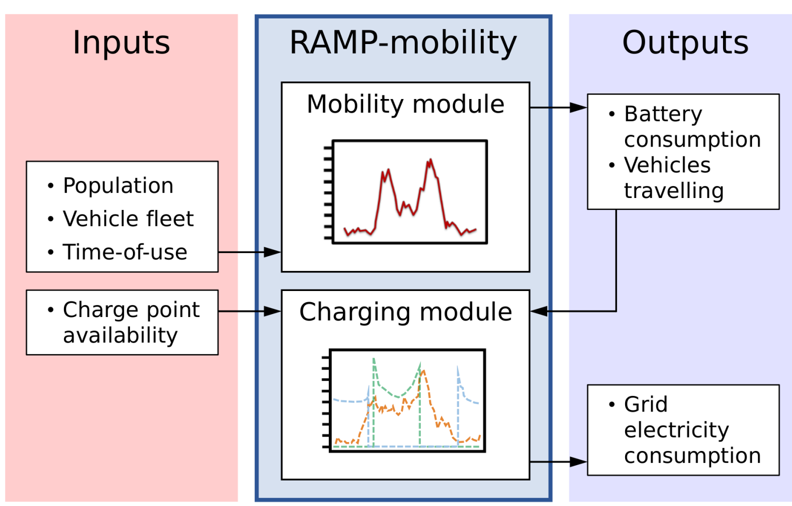

Figure 1. Conceptual scheme of the overall model structure. The model features two separate modules for the simulation of, respectively, mobility patterns and charging strategy

3.1 Mobility pattern simulation

The algorithmic approach to the simulation of mobility patterns builds on and expands our previously developed RAMP software engine [19], itself conceived for the stochastic simulation of generic demand profiles based on simple time-of-use information for different user types. Here, we expand the approach to additionally take into account vehicle fleet composition and driving-specific parameters, such as vehicle speed. Fig 2 summarises the workflow of the mobility pattern simulation module. First, input about population and vehicle fleet compositions are combined to define user-vehicle pairs. Second, each pair is associated with a different temporal behaviour for each 'day type', distinguishing between weekdays, Saturdays and Sundays (or festivities). Third, the total mobility demand for each user on a given day is computed. Fourth and final, single travels are randomly simulated until reaching an amount of travelled kilometres which equals the mobility demand of the day. Methods and assumptions supporting each step of this workflow are further detailed in the following sections.

3.1.1 User and vehicle characterisation

As shown in Fig 2, one a country and calendar year is given, the first step of the mobility module consists in building realistic users and vehicles for the simulation. By default, we divide the population of each country of application into three macro-categories of users, namely workers, students and inactive users. For each country, we simulate the representative number of 2500 total users, with the share of individual users simulated for each category being a function of the population composition, as provided by Eurostat [31, 32]. Each individual user is then associated with one of three possible electric vehicle sizes, namely small, medium and large, in such a way that each user category mirrors the country-specific vehicle fleet share [33]. A summary of all the openly-available data sources we adopt is provided in the Supporting Methods, where we also discuss how we associate to each vehicle size a different driving consumption curve and battery capacity.

3.1.2 Daily travel needs across 'functioning windows'

To model user behaviour, rather than defining chains of events with associated probabilities, the core idea behind RAMP's stochastic engine is to define *functioning windows* (see the second main block in Fig 2), or time frames in which mobility events can randomly occur. For each category of users, the model distinguishes between: *main* functioning windows, in which the main daily travels (e.g. commuting to work/study place) occur; and *free-time* functioning windows, which account for additional occasional trips. For the case of students and workers, we consider two main functioning windows, which match the commuting-related morning and evening mobility peaks recorded in the majority of time-of-use surveys across Europe [34] (Fig S10). They are complemented by free-time windows that cover the rest of the day, and in which non-work and non-study related trips may occur. Inactive users are characterised by only one main functioning window, encompassing the whole range of hours in which a person is typically awake and active in a day, and by two free-time windows for trips that occur in the early morning or during the night. The definition of main functioning windows for these inactive users grounds on the 'unspecified time use and travel' data series from Eurostat, complemented by data from JRC's mobility surveys [35]. Finally, mobility patterns are differentiated according to the day type: weekday, Saturday and Sunday (or festivity), in agreement with real-world mobility patterns [36], with workers and students behaving

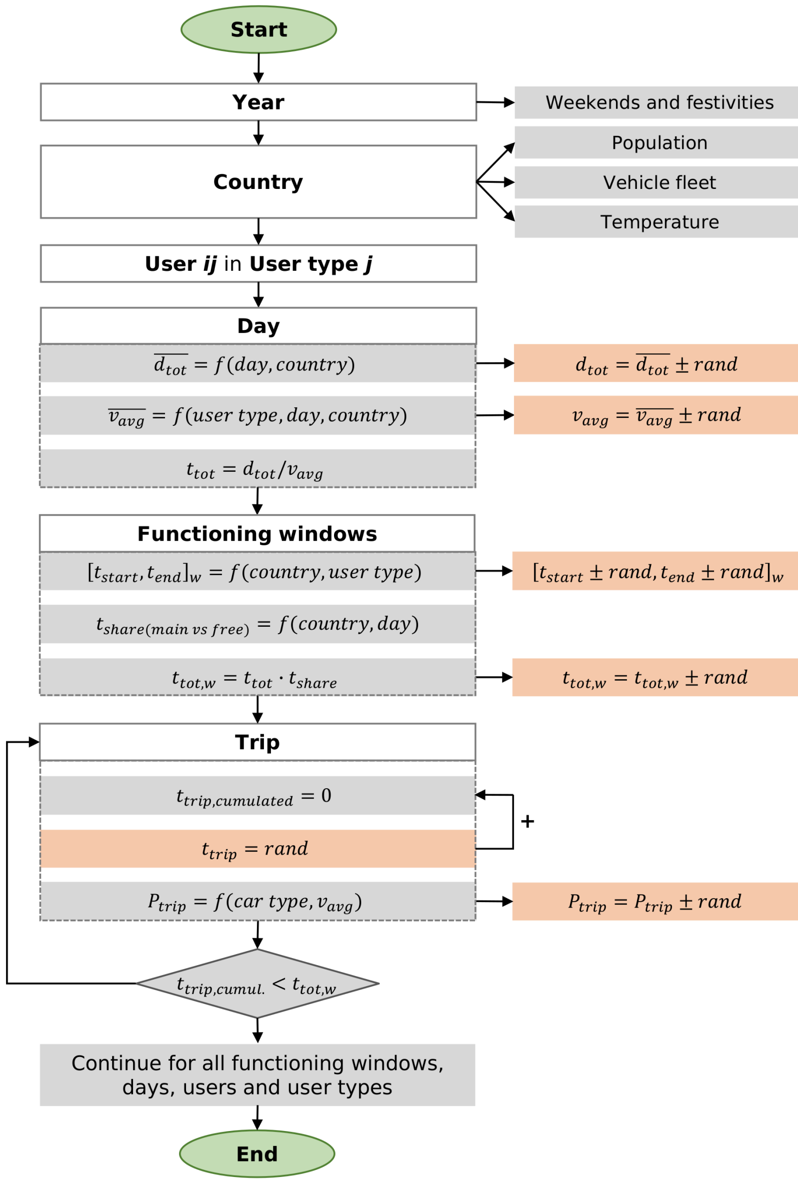

Figure 2. Workflow of the mobility pattern simulation module. Population and vehicle fleet data allow to define user-vehicle categories. For each calendar year, the day type determines the way in which peak and off-peak functioning windows are defined and how the total daily mobility demand is subdivided between those. Hence, individual travels are simulated for each user until their total daily transport demand is satisfied. Parameters subject to stochastic randomisation are highlighted in orange boxes (see also Table S2). The output of such workflow is twofold: a time series of battery power consumption for each user (and for the whole fleet) and a time series of the share of vehicles that are travelling in each time step.

similarly to inactive users during Saturdays and Sundays or festivities.

Alongside the definition of functioning windows, the model computes the total distance travelled each day (d_{tot}). More precisely, to keep coherence with the model output, which is based on time information rather than on distance, the latter is converted into a total daily time of travel (t_{tot}) multiplying it by the average trip velocity (v_{av}) (see Fig 2. Both d_{tot} and v_{av} are computed for each user and car type based on data gathered from the JRC mobility survey [37], and made subject to stochastic variability for every simulated user and day. A full list of parameters undergoing stochastic randomisation is reported in Table S2. Data for countries not covered by the JRC survey are adapted from those of neighbouring ones (Table S1). As shown in Fig 2, which fraction of d_{tot} is spent in main versus free-time mobility activities is is determined from the values of car usage percentage per hour and day type, available from the JRC survey [37] (see the Supporting Information for further details).

3.1.3 Simulation of individual trips

At this point, as shown by the 'Trip' block of the conceptual scheme in Fig 2, the algorithm simulates individual trips for each user and type of activity (main or free-time) until the total travelled distance matches the expected value for that particular type of user and activity type. The duration and average speed of each simulated trip are made subject to stochastic randomisation (Table S1). As a result, also the power consumption of the vehicle is randomised as a function of the random average velocity (and car type), as further detailed in the Supporting Methods. The process is repeated for all individual users within each user category, and for all days of the year, for each European country. As an output, the model provides the aggregate fleet battery consumption and the share of travelling vehicles in every time step, as shown in Fig 1. User-disaggregated information are as well retained for use in the subsequent charging simulation module.

3.2 Charging strategy simulation

Based on the computed user-specific battery consumption and mobility time series, the model allows to simulate for each individual user three different charging strategies, all equally allowing to meet the given battery demand. Fig 3 summarises the algorithmic logic adopted and the differences between each strategy, which are:

- **Uncontrolled charging**. Users charge their vehicle as much as possible and as soon as possible. Each time a user trip ends, a parking event begins, and the presence of the charging point is verified by means of the charging point probability (CP_{prob}) function (see Supporting Methods). If the charging infrastructure is available, the battery is charged, assuming a 90% charging efficiency at the charging point nominal power ($P_{nom,CP}$), randomly sampled from a probability distribution that reflects the relative share of different charging point types (Table S4). The charging event lasts till SOC_{max} is reached. The maximum SOC can be arbitrarily set to a value lower than 100% to avoid faster degradation of the battery [38]; in agreement with the literature, we set it at 80% [39].
- **Night charging**. Users are incentivised to charge vehicles during night hours, in such a way to avoid overloading the power system during the already critical morning and evening hours. Before the CP_{prob} function is computed, the algorithm checks the time of parking. If parking time lies in the desired night-hour window, the vehicle is charged, otherwise it is not (unless there isn't enough energy for the next trip). Furthermore, the charge doesn't occur at full power, but at the minimum power that allows to completely charge the battery during night hours, as proposed by Gaete-Morales *et al.* [26].
- **VRES charging**. Users are incentivised to charge when there is an excess of renewable generation in the area. The charging algorithm is essentially the same of night charging, except that time windows for which charging is allowed are now

based on the residual load curve, i.e. the difference between the country-wide electricity load demand and renewable (solar and wind) generation (see Supporting Methods). When the residual load is negative, renewable generation alone exceeds the electricity demand and calls for storage options, such as storage in electric vehicle batteries.

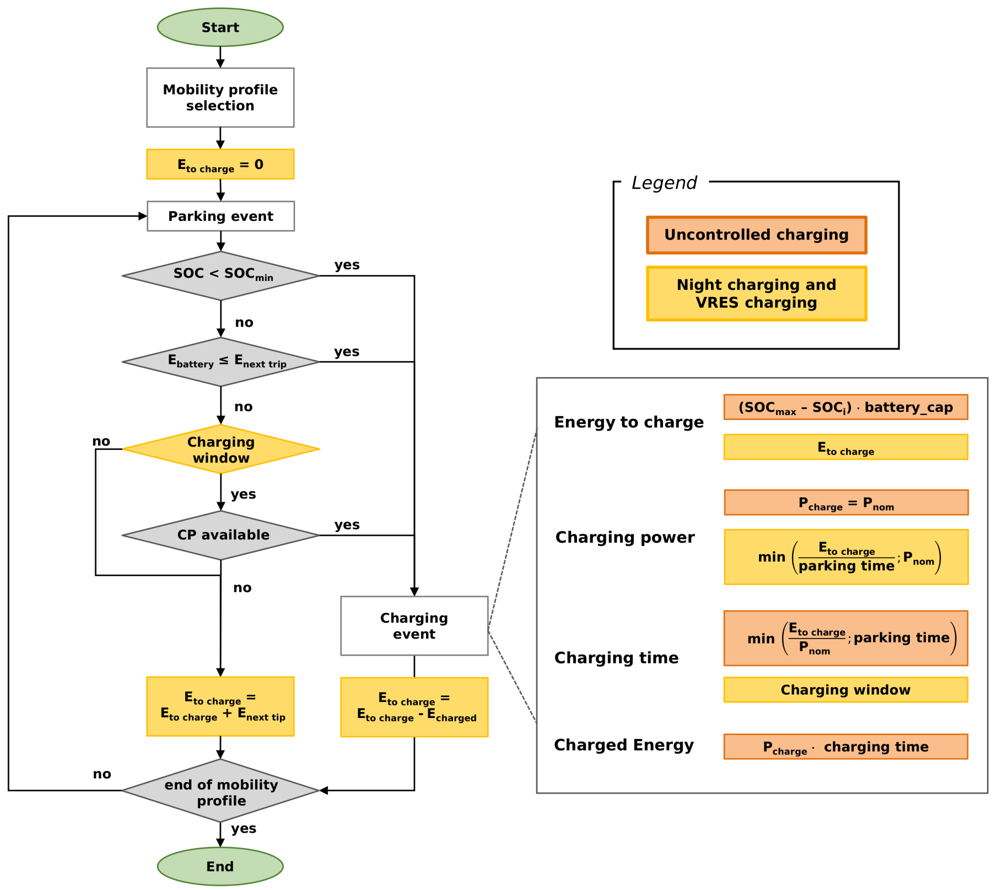

Figure 3. Workflow of the charging strategy simulation module. Colour coding is used to differentiate parts of the algorithm that pertain to uncontrolled and smart charging strategy options.

It is worth noting that mobility time series are simulated irrespective of the charging strategy, which is simulated only as a second step. Hence, it is not excluded that a vehicle state of charge reaches negative values, violating real-life physical constraints. For this reason, as shown in Fig 3, the algorithm for the charging simulation module features two checks that prevent such possibility. First, we define a minimum state-of-charge value (SOC_{min}), below which the user is forced to charge the car as soon as parked. Second, we check that the energy stored in the battery is sufficient to cover the upcoming trip - or, the upcoming two trips in case the car is going to be parked only for a brief (shorter than 10 minutes) stop.

In addition to the charging strategy, the model user is free to customise vehicle types (see Table S3 for default ones), the CP_{prob} function and the charging-point availability anxiety. For further details about such customisation options, we refer the reader to the Supporting Methods.

3.3 Empirical data and validation criteria

The following sub-sections discuss: i) the features of the metered data which the model is tested against; ii) the model set up to allow a meaningful comparison with such data; and iii) the metrics we define to compare simulated and metered data.

3.3.1 Empirical data

RAMP-Mobility results are validated against real-life charging transactions metered in the Netherlands by ElaadNL between January 2012 and May 2016, as processed by previous work [40]. The year selected for validation purposes is 2015, i.e. the most recent full year of available data. As described by Beltramo *et al.* [40], raw data consisted in user-specific charging transactions from around 1750 charging points, which represent roughly 16% of the whole public charging infrastructure available in the Netherlands at the time of metering. Since the data included not only electric vehicle charging transactions, but also plug-in hybrid electric vehicles', which are not in the interest of purely-electric vehicle analyses, the dataset was processed to filter only the transactions representing frequent electric vehicle users. More precisely, plug-in hybrid electric vehicles' transactions were identified (and removed) as those characterised by a maximum charging power lower than 4 kW and maximum charged energy lower than 12 kWh. In addition, users having less than 10 transactions overall were disregarded. This translates into a useful dataset of 2215 users (accessible via Zenodo [41]), 60% of which owning small and 40% large vehicles. The data also show that the CPs have an overall maximum nominal power of 12 kW, with the vast majority (around 80%) actually supplying power at 3.7 kW maximum, another 15% in the range of 8-12 kW, and the rest being evenly distributed along the other values.

It is worth noting that an analysis on the same dataset by Helmus *et al.* [42] showed that, whilst day-time transactions tend to occur at any random charging point, night-hour transactions tend to take place at charging points installed upon explicit user request nearby their homes, and used with similar logic as private charging points. As such, the ElaadNL dataset approximates the characteristics of both public and private charging in different moments of the day.

3.3.2 Model settings alignment to dataset

For testing against such data, RAMP-mobility default settings for the Netherlands are aligned to the specific characteristics of the population considered within the validation dataset. First, we align the car fleet share and charging point power distribution to those discussed in the previous paragraph. Second, to reflect the higher probability of finding a charging point close to home in periods other than main-activity hours, we adopt a piecewise CP_{prob} function instead of the default constant value (see Supporting Methods). In addition, acknowledging the high degree of uncertainty surrounding the precise definition of a piecewise CP_{prob} function, we perform a sensitivity analysis around plausible values of the latter. More precisely, as shown in Table S5, we identify 9 sensitivity cases by varying the four parameters which define the curve shape – the higher/lower probability values, and the hour of the day at which they switch.

3.3.3 Validation metrics

The comparison between simulated and metered profiles is carried out for non-dimensional profiles, obtained by normalisation with respect to the total yearly energy consumption. In fact, while RAMP-mobility will simulate all of the charging transactions experienced by each user, the validation dataset only accounts for those transactions occurred in one of the public CP owned by ElaadNL (16% of the total). It is hence 'blind' to possible additional transactions experienced by the same users through other utilities, preventing a dimensional comparison. The accuracy of the model is assessed with two parameters, the Root Mean Square Error ($RMSE$) and the average Load Factor ($\overline{LF}$), as defined in Equations 1-2.

$$RMSE = \sqrt{\frac{\sum_{t}^{N_t}(P_{model}(t) - P_{measured}(t))^2}{N_t}} \tag{1}$$

$$\overline{LF} = \sum_{d=1}^{365} \frac{P_{average}(d)}{P_{peak}(d)} \cdot \frac{1}{365} \tag{2}$$

The $RMSE$ allows to evaluate the minute-by-minute deviation between simulated and measured data, and can be applied to both the charging profile curve and to the load duration curve. In Equation 1, $P_{model}(t)$ and $P_{measured}(t)$ are, respectively, the charging power computed by the model and the one metered from ElaadNL (both normalised with respect to the integral of each curve, i.e. the total energy consumption over the year); N_t is the total number of timesteps in a year. The average Load Factor ($\overline{LF}$) provides an additional, alternative way to compare simulated and measured charging profiles in terms of their peak-to-baseload ratio [19]. Averaged across every day (d) of the year, $P_{average}(d)$ is the daily average power consumption for charging and $P_{peak}(d)$ is the daily peak power consumption. For the computation of this parameter, average and peak power consumption are computed with respect to hourly-resampled timeseries, in such a way to smooth out possible anomalies due to steep peaks lasting only for one or few minutes.

3.4 Europe-wide long-term simulations

With application to the generation of Europe-wide mobility and charging time series for long-term energy modelling scenarios, we adopt the following model parameters and assumptions. Unlike for the validation case, which needed to reflect specific infrastructure characteristics of present-day electric mobility in the Netherlands, we assume a time-invariant CP_{prob}, by default set to 80%. We assume charging stations to be distributed with a higher share of 3.7 and 11 kW nominal power stations (respectively, 60% and 30% of the total), and a more restricted number of 120 kW superchargers (the remainder 10%). We simulate 2500 users - having verified that a higher number would not produce substantially different aggregate results - for each country, leading to a total of 70000 users for the whole Europe. User category and vehicle-type shares in each country are assumed not to vary with respect to present data. We do not use the optional logistic function implemented in the model to simulate a more relaxed user behaviour with respect to charging-point availability anxiety (see Supporting Methods), due to a too high uncertainty associated with the parameters defining such function. The datasets adopted for characterising users behaviour and vehicle fleets are the same as those outlined in sub-section 3.1 and in the Supporting Methods.

3.4.1 Plausible scenario variations

In addition to the aforementioned assumptions, which constitute our reference scenario for long-term electric vehicle demand simulation, we consider a number of scenario variations which allow assessing the impact of plausible future developments in the field of electric vehicle integration.

First, we consider a 'smart-charging' scenario in which we assume users to adopt a diverse mix of charging strategies, including smart ones, in opposition to the reference case in which we assume only uncontrolled charging. Each charging strategy is assumed to be adopted by a certain share of the population. For night charge, such share corresponds to the percentage of population living in detached houses [43], which are more likely to be provided with a private parking lot. The share is kept constant (and equal to the EU average) across all countries in order to ensure that results are comparable. The share of VRES-charging cars is set to 10% for all selected countries, which is a conservative estimation with respect to the levels of vehicle-to-grid participation assumed, for instance, by the IEA (which would be above 15% for European countries) [16]. The combination of night- and VRES-charging vehicles provides a total of 44% of the fleet adopting smart charging strategies, with the remaining 56% assumed to adopt an uncontrolled charging strategy.

Second, we consider plausible scenarios of sharp technological (battery capacity) and infrastructure (charging point power ranges) development. For batteries, forecasts for 2030-2035 envisage an increase of gravimetric densities in the range 325-500 Wh/kg, depending on the battery chemistry [16, 44, 45]. Further improvements might be brought about by the yet-to-be-commercialised solid-state, lithium-sulphur and lithium-air batteries, which could ensure gravimetric densities of about 800-1000 Wh/kg in the long run (2050-2070) [44]. Here, we assume improvements in line with the target of 500 Wh/kg, as further detailed in the Supporting Methods. For the charging infrastructure, we assume reference power levels (Table S4) to be upgraded to, respectively, 7 kW, 150 kW and 350 kW. The entry level (7 kW) refers to the maximum charging power for single phase AC wall-boxes [46]. A 150 kW in DC supply is instead already supported by most advanced electric vehicles on the market, such as Audi e-tron 50 and 55 quattro, Audi e-tron Sportback 55 quattro, BMW iX3, Ford Mustang Mach-E ER and Volvo XC40 Recharge. Some models, such as Porsche Taycan and Tesla models already have DC charging limits higher than 200 kW. Finally, the top charging power level of 350 kW since represents the maximum power rate of Ionity infrastructure that represents the European ultra-fast charging network.

Table 1 summarises all the considered scenarios.

Table 1. Summary of assumption variations across all the considered scenarios.

	Reference	**Smart charging**	**Battery upgrade**	**Charging upgrade**	**Battery & Charging upgrade**
Mix of charging strategies	no	yes	no	no	no
Battery developments	no	no	yes	no	yes
Charging infrastructure developments	no	no	no	yes	yes

3.4.2 Additional metrics and scaling to whole-fleet absolute values for cross-country comparisons

To allow an immediate understanding of the impact of electric vehicle loads on power systems across Europe, we define an ad-hoc metric. Such metric is the ratio between power system peak demand with and without the additional load entailed by electric vehicles. Such peak ratio is computed separately for each day of the year, and then averaged throughout the entire year, as shown in Equation 3.

Performing such calculation entails turning the generated non-dimensional electric vehicle demand profiles into corresponding dimensional profiles. To this end, we consider a mass-scale deployment of electric vehicles, such to replace the entire existing fuel-based vehicle fleet in each country. We gather the overall passenger kilometres travelled (pkm) for each country (assumed equal to 2018 values [47]) and divide those by the average occupancy rate (set to 1.7 for all countries [48]), thereby obtaining the total vehicle kilometres travelled (vkm) by country. Hence, we translate vehicle kilometres into energy units by dividing those by the specific electricity consumption per kilometre, which we assume equal to 0.20 kWh/km for each country (roughly corresponding to the average consumption of models currently available on the market [49]). The power system baseline electricity demand is assumed being equal to that provided by ENTSO-E for each country for the year 2016 [50]. Since ENTSO-E data have hourly resolution, dimensional electric vehicles demand profiles are also resampled to hourly resolution before computing the ratio.

$$Peak\,ratio = \sum_{d=1}^{365} \frac{P_{max}^{(ENTSO\text{-}E+EVs)}(d)}{P_{max}^{ENTSO\text{-}E}(d)} \cdot \frac{1}{365} \tag{3}$$

4 Results

The following sub-sections present and discuss our results. First, we discuss how well the model compares to metered data. Second, we show the electricity consumption that would be entailed by an uncontrolled deployment of electric vehicles in Europe, discussing differences across countries. Third, we show to what extent smart charging could mitigate such consumption figures and their impact on current peak electricity demand in each country. Fourth and final, we investigate the potential effects of technology and infrastructure developments on such results.

4.1 Validation

Fig 4 shows the comparison between the sensitivity cases discussed in paragraph 3.3.2 and the metered ElaadNL data. A satisfying match can be noticed for a large portion of the curve, with larger deviations experienced for the tails representing highest and lowest values. As regards lowest values, representing the night-hour charging load, the ElaadNL dataset often experiences a null load as opposed to a slightly non-null load expected by RAMP-mobility (see Fig S1). In fact, the limited number of users populating the ElaadNL dataset leads to a total absence of load during some hours of the night which would be, however, less realistic if dealing with a country-scale pool of electric vehicle users. When considering the highest values, significant deviations are only experienced for two sensitivity scenarios, namely those in which the timing of the evening step of the CP_{prob} function is varied, demonstrating a highly accurate match in all other cases.

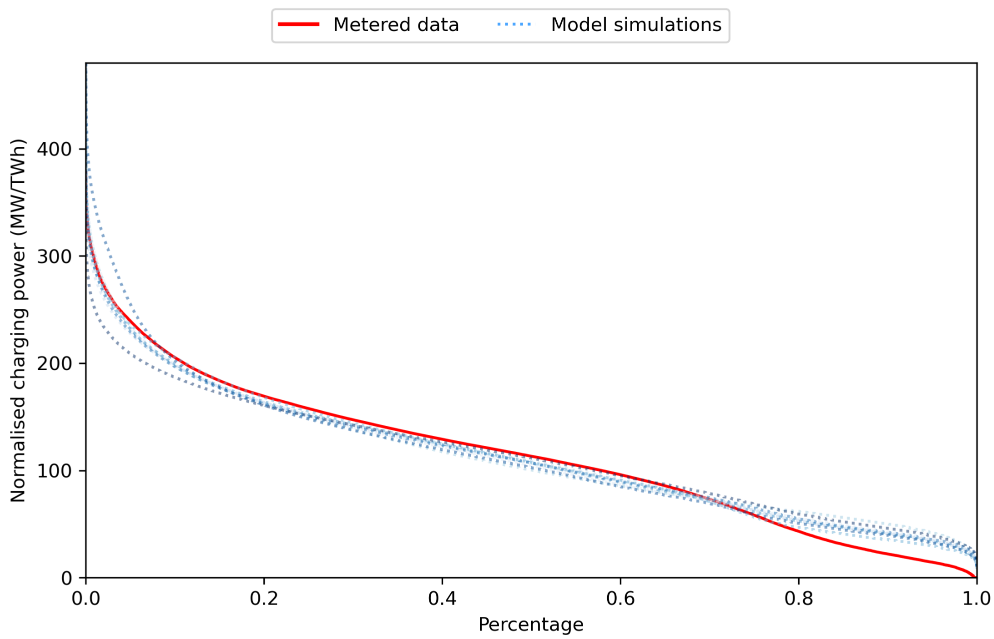

Figure 4. Comparison of metered and simulated data. Data are shown in the form of load duration curves, with a 1-min time resolution. Simulated data are represented by 9 curves, representing the reference and the 8 sensitivity cases for the piece-wise probability function reported in Table S5.

In Table 2, the quantitative parameters calculated are presented for the reference case and for all the 8 sensitivity cases. The relative error between simulated and metered data in terms of $\overline{LF}$ is of about -9.2% in the reference case, ranging from -22% to 7.3% across all sensitivity cases. For most cases, however, the percentage error is negative and lies in a narrower range, between -5% and -13%. This highlights a general tendency of RAMP-mobility to have a higher peak-to-baseload ratio compared to the ElaadNL dataset. The analysis of charging profiles in Fig S1 also suggests that a large part of this deviation is attributable to the period of summer vacation (July-August), in which the metered peak consumption decreases. Since behaviour change during summer vacation is not accounted for in RAMP-Mobility, this leads to a more marked deviation between metered and simulated data in that period.

The $RMSE$ also shows consistent results for both the charging demand time series and load duration curve. For the time series, the $RMSE$ ranges between 13.6% and 15.8%, with the reference case having a value of 14.2%. Such an order of magnitude can be viewed positively, considering that a difference between two time series in a single time step can lead those to diverge for several of the subsequent timesteps, thereby increasing the RMSE despite negligible practical differences. Indeed, the $RMSE$ computed on the LDC is significantly smaller, ranging from 1.7% to 4.1% and having a reference value of 2.6%. This is because the distributional nature of the LDC allows precisely to smooth out unwanted effects like those aforementioned.

4.2 Electric mobility and charging profiles across Europe

We can hence move forward to analysing results in terms of charging profiles across all the considered European countries, based on the reference scenario assumptions defined in sub-section 3.4. For simplicity, we categorise countries in 8 macro-regions, for

Table 2. Quantitative comparison between metered and simulated data, for the reference case and for the 8 sensitivity cases. The comparison is performed in terms of relative error in the Load Factor calculation, as well as in terms of $RMSE$ – the latter computed for both the time series and the load duration curves.

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9
LF error [%]	-9.2	-13.1	-5.1	-12.9	-5.7	-9.9	-8.8	-22.0	7.3
RMSE timeseries [%]	14.2	14.1	14.5	13.6	15.8	14.1	14.6	15.0	14.7
RMSE LDC [%]	2.6	2.9	2.5	3.8	1.7	2.4	2.8	3.7	4.1

each of which we show in Fig 5 the results of the respective 'most-representative' country (see Table S6).

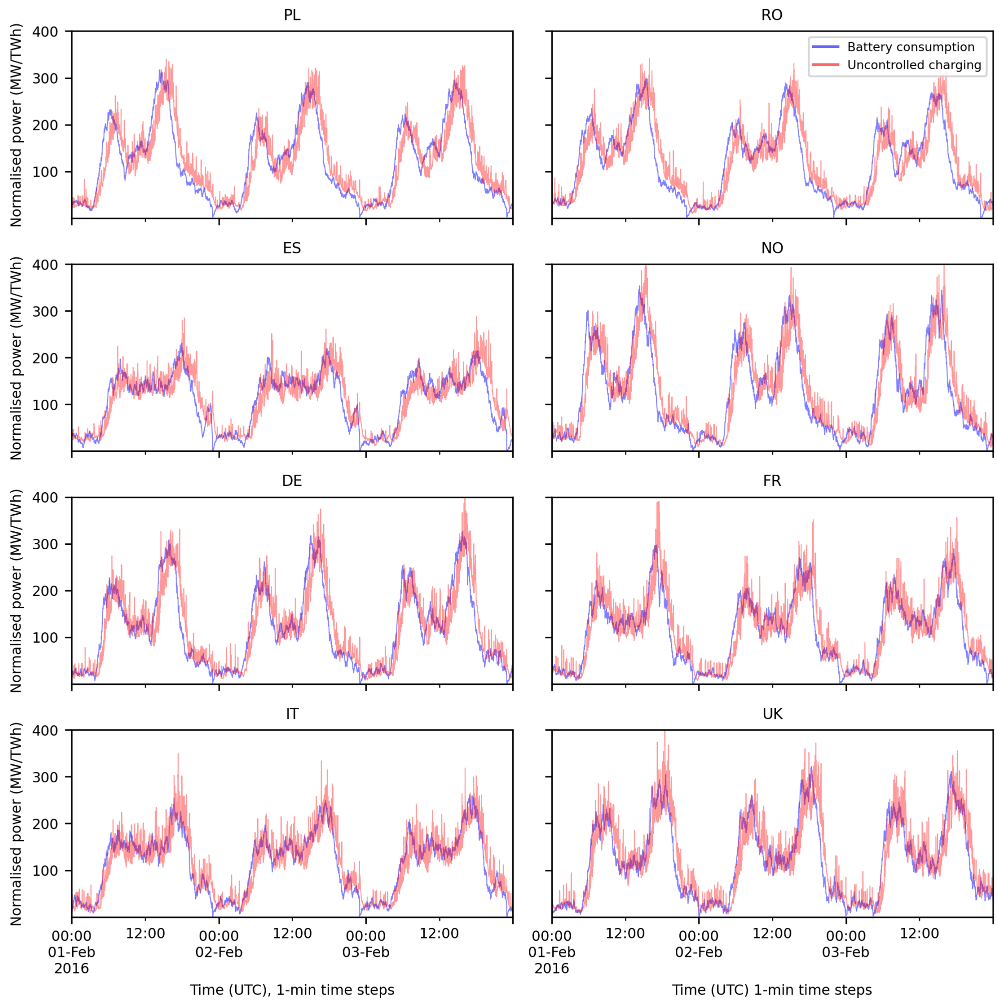

Figure 5. Uncontrolled battery consumption and charging power. Time series of battery consumption and charging power of an electric vehicle fleet in representative European countries for users adopting an uncontrolled charging strategy. All power consumption figures are normalised with respect to an annual energy consumption of 1 TWh. Results are here shown for a three-day representative winter period (February), while results for all other seasons are provided in Fig S2-S4.

As expected, 'uncontrolled' charging power demand time series follow, for each country, the same temporal pattern as battery consumption, albeit delayed in time. On the other hand, such temporal patterns experience marked differences across countries.

Most countries are characterised by a double-peak daily profile, with morning and evening peaks driven by working and/or student types of users. Countries in which these peaks are particularly pronounced, such as Norway, have indeed the highest relative share of workers and students in their pool of electric vehicle users; conversely, countries with substantially flatter profiles, like Italy and Spain, are those with the lowest relative share of such users. These results highlight the key role that country-specific user types and behaviours have in determining the shape of the electricity demand profile associated with large electric vehicle pools, suggesting that the common practice of relying on a single 'standard' profile or dataset for several different countries might lead to substantial errors.

Differences across countries in terms of battery consumption peaks are, in addition, driven by differences in weather conditions, with particularly cold or particularly hot weather both leading to increased battery consumption. For instance, we see that the peak in Norway or Germany can be up two twice as much as the peak in Italy or Spain in the winter (Fig 5), due to the combined effect of higher share of active users and colder weather in the former countries; on the other hand, such difference can be substantially less marked, or even reversed, in the summer (Fig S2). This stresses even more the importance of adopting country-specific datasets to generate bottom-up electric vehicle demand profiles, including weather-year information that are consistent with those adopted for renewable generation patterns.

4.3 The impact of smart charging

Differences across countries in electric vehicle demand profiles gain further nuances if considering not only uncontrolled charging, but rather a mix of charging strategies, including smart ones. In particular, as shown in Fig 6 (and, at higher temporal resolution, in Fig S5), while profiles tend to be rather similar across countries for users adopting a 'night-charging' strategy, substantial differences are experienced for users following 'VRES-charging' strategies. Such type of users behave completely differently depending on the availability of VRES in the associated country and in each day, for instance concentrating the electric vehicle charging in the central hours of the day when there is an excess of PV generation - as visible, for instance, in Fig 6 for Italy and Spain, or for Germany for the first 2 representative days - or during the night when there is an excess of wind generation - as it occurs, for instance, in Fig 6 for Poland and Germany before the second and third representative day, respectively. What is most interesting, however, is that the presence of users adopting either night- or VRES-smart-charging strategies does contribute to smoothing out charging demand peaks, which is critical to enable a frictionless integration of electric vehicle charging infrastructure into power systems. The same holds for other seasons, as shown in Fig S6-S8.

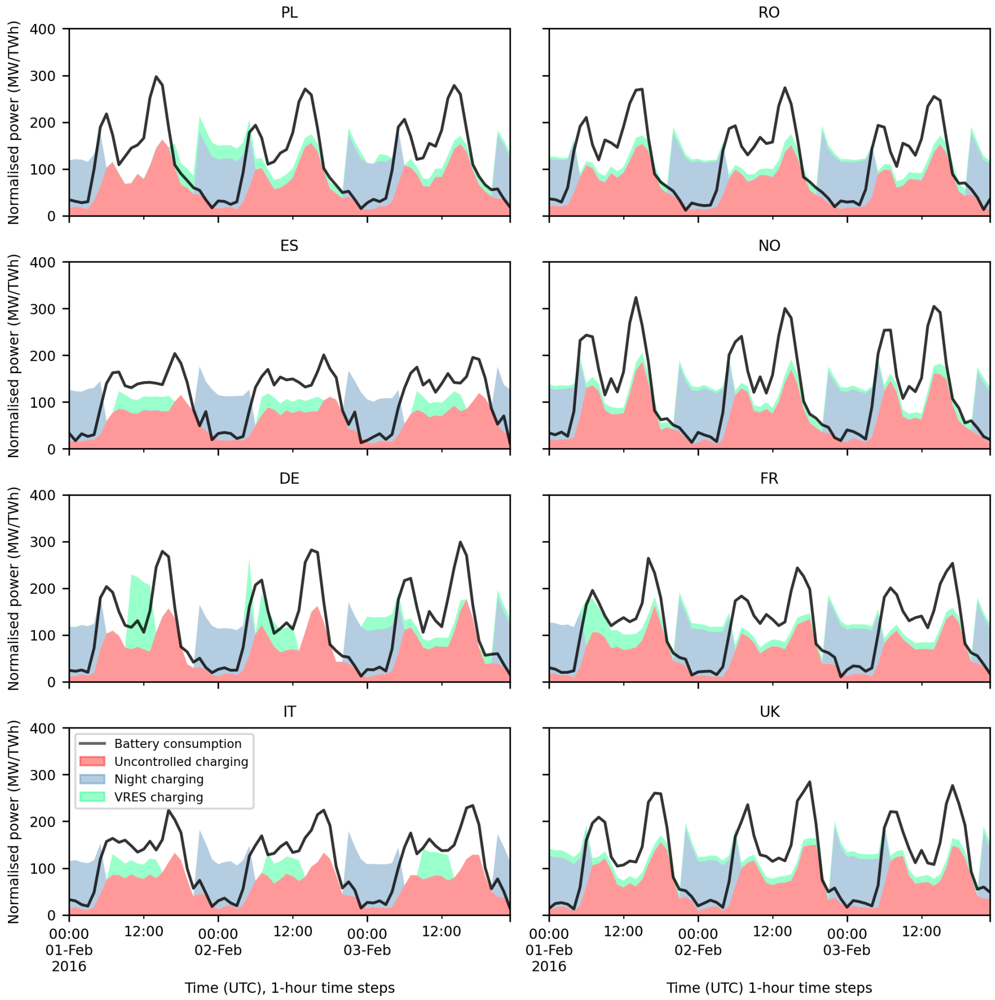

Figure 6. Mix-of-strategies battery consumption and charging power. Time series of battery consumption and charging power of an electric vehicle fleet in representative European countries assuming a mix of charging strategies. Colour coding differentiates the contributions of subset of vehicles adopting different charging strategies (uncontrolled, night and VRES charging) to such total consumption figures. All power consumption figures are normalised with respect to an yearly energy consumption of 1 TWh. The same results for other periods of the year are provided in Fig S6-S8.

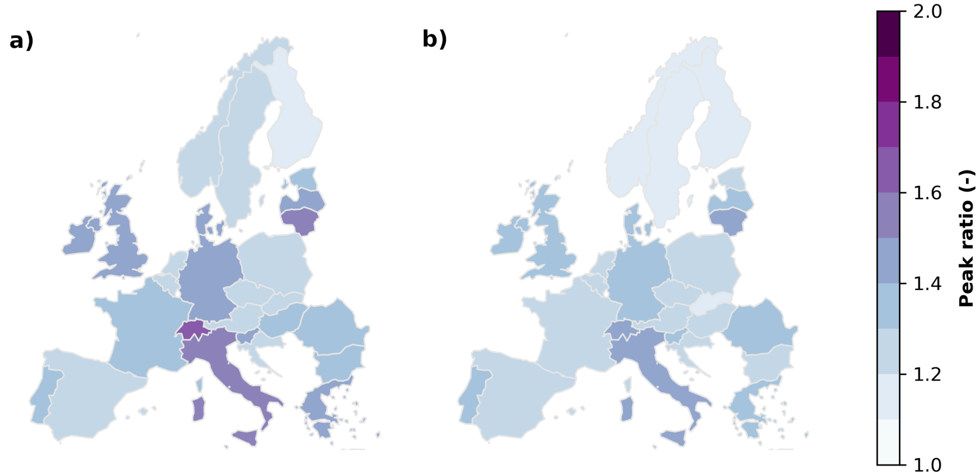

Figure 7. Peak ratio. The peak ratio (see Equation 3) is shown for users adopting an 'uncontrolled charging' strategy (**a**) and for for users adopting a combination of uncontrolled-, night- and VRES-charging strategies(**b**). Countries left blank are those not covered by our data set.

Fig 7 shows to what extent the introduction of smart-charging mechanisms, such as night- and VRES-charging, would be effective in reducing the additional burden on the power system as a consequence of a massive deployment of electric vehicles. An 'uncontrolled' deployment of electric vehicles could increase by 36-to-51% the daily peak demand to be met by the power system (on average, throughout the year) for industrialised and densely populated countries like France, Germany, Italy and the United Kingdom. Conversely, a deployment which features non-negligible shares of night-charging and VRES-charging users would lead to an increase of only 30-to-41% for the same countries. The result is particularly relevant if considering that smart charging strategies are here simply simulated according to plausible shares (see sub-section 3.4) rather than being actually optimised with respect to power system operation. Potentially, more marked improvements could be attained by endogenously optimising the charging behaviour within a power system model, and using the obtained 'optimal' behaviour to inform the practical shaping of ad-hoc V2G schemes.

4.4 The impact of technology and infrastructure developments

The considered plausible developments in terms of battery capacity and charging infrastructure power do not seem to lead to significant changes in the characteristics of electric vehicle demand profiles. As shown on the left-hand side of Figs 8 and S9, larger batteries do not produce any relevant change in the aggregate charging load, whereas more powerful charging points lead to higher instantaneous peaks at the minute scale, which nonetheless largely smooth out when looking at the hourly scale.

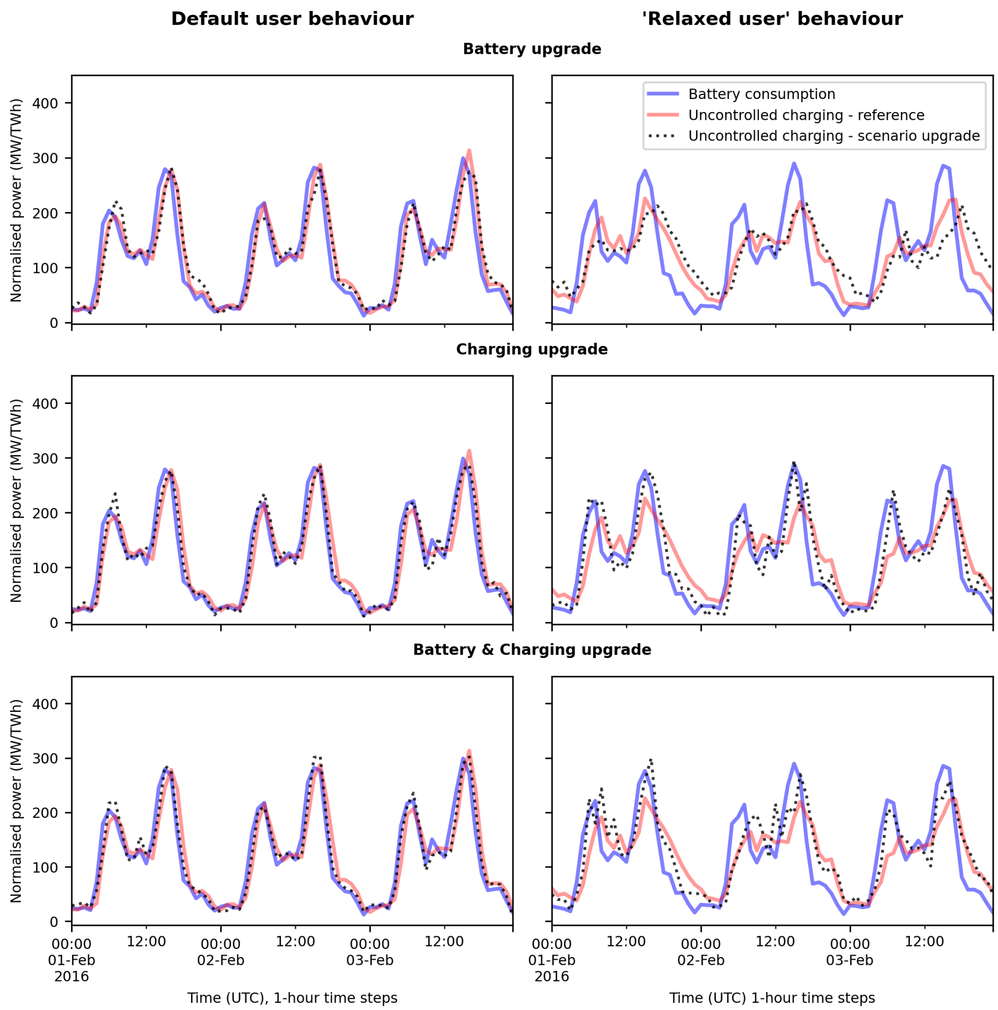

Figure 8. Battery consumption and charging power across plausible infrastructure and technology development scenarios. Time series of battery consumption and charging power of an electric vehicle fleet in Germany for the reference scenario (uncontrolled charging) and for scenarios assuming plausible technology and infrastructure developments (battery upgrade, charging upgrade, or both - see Table 1). Results are shown for the alternative cases in which a more relaxed user behaviour with respect to the anxiety of finding a charging point is not considered (left) or considered (right). All power consumption figures are normalised with respect to an yearly energy consumption of 1 TWh and resampled to hourly time steps.

This might be seen as an artifact of the assumed user behaviour: by default, users tend to charge as soon as parked, which does reflect the typical behaviour of an electric vehicle user in case the charging infrastructure is not as widespread as its fuel-based counterpart (as demonstrated by the validation against empirical data discussed in sub-section 4.1). However, this might insufficiently reflect the more 'relaxed' behaviour of future users that safely rely on a fully developed charging infrastructure. If the built-in optional 'relaxed user behaviour' functionality is allowed (see sub-section 3.4), the same technology and infrastructure developments entail non-negligible changes in the shape of charging profiles (right-hand side of Figs 8 and S4). More precisely, if users charge their vehicles only when approaching a low level of charge (i.e. as they are more 'relaxed' with respect to the chances of finding a charging point exactly when needed), upgraded batteries lead to a relatively more pronounced smoothing of peaks than in the baseline. In fact, having a more energy-dense battery for the same consumption pattern entails a delay in the moment of perceived necessity of charging, which in turns leads to more diluted charging events at an aggregate level. Interestingly, however, the simultaneous availability of a more powerful charging infrastructure (which is just as likely to occur) more than compensates for such profile-smoothing effect provided by more energy-dense batteries. This confirms that, irrespective of whether the user 'anxiety' with respect to the charging infrastructure in a long-term future is relaxed, the expected technology and infrastructure developments are not likely to play a key role in defining the shape of future charging demand patterns at country-scale.

Conclusions

Policy decisions pertaining to the mass-scale deployment of electric vehicles for integration with the power system are currently slowed down by unanswered questions concerning the impact that such a deployment would have on electricity demand and the potential of smart charging mechanisms to mitigate it [13]. This is particularly relevant for Europe, whose diversity of socio-economic and weather conditions across member countries calls for country-specific answers to the aforementioned questions despite common targets and ambitions.

In this work, we try to address precisely such questions. To this end, first, we have developed a model that allows to simulate electric vehicle battery consumption and charging time series based on a restricted set of widely available data, which makes it easily adaptable across contexts, such as across all European countries and beyond. Second, thanks to the availability of empirical data of electric vehicle charging in the Netherlands, we have tested the model against pertinent real-life figures, demonstrating a good accuracy of the latter across a number of quantitative metrics. Third, we have applied the model to simulate long-term scenarios of highly-resolved electric vehicle consumption and charging time series for all European countries.

The application of the model showcases that such time series experience substantial variations across countries, due to the combined effect of socio-economic (e.g. relative predominance of students and commuting workers in each population) and weather-related (e.g. outdoor temperature trends) factors. This result is particularly relevant as it proves the inaccuracy of the common practice of considering a single, standard time series as representative of all European countries. Furthermore, when considering vehicle demand time series as an input for power system optimisation models, it stresses the need for simultaneously generating them together with those pertaining to renewable generation, based on a common set of weather years. The energy modelling community should hence acknowledge the need for using country-specific and weather-explicit electric vehicle consumption and charging input time series, which our work now makes freely and openly available.

Regarding the potential impact of electric vehicle on existing power systems, we show that the latter could be significant with an 'uncontrolled' deployment of electric vehicles. In such a case, the increase in the daily peak demand to be met by the power systems lies in the range 36-51 %, depending on the specific country. On the other hand, supporting the adoption of smart charging could be a highly effective means for smoothing out charging demand profiles from large fleets of electric vehicles. Plausible shares of users adopting smart charging strategies could in fact limit peak demand increase to the range 30-41%. For Germany, for instance, this would mean in practice a reduction in the average daily electricity demand peak of about 6 GW. Stronger benefits could be achieved through strong political support for larger-than-assumed adoption of smart charging strategies, in combination with a marked expansion of renewable generation capacity, as well as by identifying even 'smarter' vehicle-to-grid strategies as a result of the joint optimisation of vehicle charging and power system operation within power system models. We thus encourage energy modellers to pursue further research in this direction and further highlight the untapped potential of smart charging, especially in combination with renewable capacity expansion.

We also show that plausible developments in battery energy density and in charging-point power would not lead to substantial modifications of the demand pattern to be handled by the power system, even if assuming more sophisticated user behaviour with respect to the 'anxiety' of finding an available charging point when needed. This confirms that political efforts for sectoral integration between electric vehicles and the power system should primarily focus on the large-scale implementation and support of smart vehicle-to-grid mechanisms.

Although providing a better understanding of the questions associated with the long-term, mass-scale deployment of electric vehicles across all Europe, the approach presented here has potential for further enhancement. First, the validation against empirical electric vehicle charging data, despite representing a key advantage of our approach compared to the majority of existing alternatives, would benefit from an expansion across several contexts, user and vehicle types. Second, simulating the evolution of user behaviour in a future in which the electric vehicle infrastructure is significantly more widespread might be useful to further enlarge the range of plausible results. In the current model, the parametrisation of such behaviour remains largely arbitrary, and would benefit from further insights from social-science research in this direction [51]. Finally, the model lends itself to a functional coupling with most recent lumped-parameter electric vehicle consumption models [52], which could be used to further enhance our representation of some technical dynamics, such as vehicle-consumption fluctuations due to ambient temperature.

In its present state, our approach already provides a first-of-its-kind validated option for the simulation of electric vehicles consumption and charging time series for the whole Europe and beyond, capable of accounting for country-specific socio-economic and weather-related factors. The fully open release of all code and data on GitHub, accompanied by a walkthrough documentation for results reproduction, ensures that the approach is widely applicable, while at the same time providing full freedom for the users to customise parameters and assumptions. Finally, the simplicity of the data required for running the model, makes the latter easy to apply worldwide, even beyond Europe.

Supporting information

S1 Fig. Model validation across months. Time series comparison between model results and empirical data for validation purposes. Results show a representative week for each month of the year.

S2 Fig. Uncontrolled battery consumption and charging power in summer. Related to Fig. 5, repeats the same results for a representative summer three-day period.

S3 Fig. High-resolution mix-of-strategies battery consumption and charging power in winter. Related to Fig 6, shows the same results at higher (1-min) resolution.

S4 Fig. Mix-of-strategies battery consumption and charging power in summer. Related to Fig 6, repeats the same results for a representative summer three-day period.

S5 Fig. High-resolution battery consumption and charging power across plausible infrastructure and technology development scenarios. Related to Fig 8, shows the same results at higher (1-min) resolution.

S6 Fig. Example of functioning time frames calculation for workers in the Netherlands. The *main* time frames are highlighted in green, the rest of the day is considered as *free time*, and highlighted in yellow.

S7 Fig. Piece-wise probability function. Default version of the piece-wise probability function to model charging infrastructure availability.

S1 Table. Overview of data sources for each country.

S2 Table. Overview of parameters subject to stochastic variability.

S3 Table. Reference models for car battery capacity depending on the car size. Data gathered from manufacturer datasheets.

S4 Table. Reference values for the charging infrastructure nominal power and relative share in each country.

S5 Table. Sensitivity cases. Overview of the nine sensitivity cases of the piece-wise probability function for the validation against empirical data from the Netherlands.

S6 Table. Macro-regions. Definition of 8 macro-regions with an associated representative country, for an easier representation of results.

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