# From fossil fuel to electricity: studying the impact of EVs on the daily mobility life of users (Extended Version)

Mirco Nanni, Omid Isfahani Alamdari, Agnese Bonavita, Paolo Cintia

*Abstract*—**Electric Vehicles (EVs) currently provide a major opportunity to decarbonize urban areas and improve their quality of life, however, the mass transition towards electric mobility requires understanding and solving the potential issues that they might cause to users. In this work, we propose a process that, through a mix of mobility data analytics, efficient trip planning, and simulation heuristics, is able to analyze the current fuel-based mobility of a user and quantitatively describe the impact of switching to EVs on their mobility lifestyle. We apply our process to a large dataset of real trips, analyzing both the impact of EVs on the collectivity and on the individuals, providing a case study with insights at the level of single users.**

*Index Terms*—**Electric vehicles, Individual Mobility Networks, Mobility Data Mining, Trip planning.**

This is an extended version of the paper published in IEEE Transactions on Intelligent Transportation Systems, containing auxiliary material and details omitted in the original paper due to space limits. This extended version is available on the GitHub page of the project, where the software and a tutorial to use it are also provided: https://github.com/alamdari/EVSim.

This work is partially supported by the European Community H2020 programme under the funding scheme *Track &Know*, G.A. 780754, and Horizon Europe research and innovation programme under the funding scheme *Green.Dat.AI*, G.A. 101070416.

Mirco Nanni is with CNR-ISTI, Italy (e-mail: mirco.nanni@isti.cnr.it). Omid Isfahani Alamdari is with the University of Pisa, Italy (e-mail: isfahany@gmail.com). Agnese Bonavita is with Scuola Normale Superiore, Italy (e-mail:agnese.bonavita@sns.it). Paolo Cintia is with KODE, Italy (e-mail: paolo.cintia@gmail.com)

## I. Introduction

Electric mobility is one of the main advocated solutions for making urban environments ecologically more sustainable, improving the quality of life of citizens [1]. Despite the quick development of the Electric Vehicle (EV) market and the strong commitment of car makers, various social barriers need still to be overcome to complete the transition of mobility towards electric [2]. Indeed, most users are very little familiar with what driving an EV really means and what it might change in their daily lives if they replace their fuel-based vehicle with an electric one. This lack of knowledge causes several worries to the average potential user, even though its many advantages for the environment are clear.

**What makes EV mobility different.** From the viewpoint of the end user, a major issue of battery-powered vehicles is their reduced autonomy. While recent years witnessed great improvements in EV technology, currently an average EV model still has a range that is around half of its fossil fuel counterpart, often inducing in the user the so-called "range anxiety" [3], which might be reduced by gaining experience in range management and building trust in range estimation systems. In addition, the time required to fill a fuel tank is usually just a few minutes, while a stop to recharge the battery of an EV can take much longer times, up to some hours, depending on the capacity of the battery and the type of recharger [4]. This requires more careful planning of trips and recharges. Finally, in most countries the recharge infrastructures are currently much less developed than fossil fuel ones, thus arising further concerns about the capability of a user to satisfy their mobility needs without introducing significant deviations from original travel plans. On the positive side, different from conventional fuel, electric energy is a utility available in any building. In several cases that makes EV recharging possible at home or at workplaces.

**Objective and novelty of our study.** This paper proposes a process that, through a mix of mobility data analytics, ad hoc trip planning and simulation, can analyze the current fuel-based mobility of a user and quantitatively describe the impact of switching to EVs on their mobility lifestyle. We emphasize that our aim is to reproduce the study over large sets of users and long periods of time, thus the process needs to be scalable and completely automatic. The final result is not only a set of general indicators over the whole population under study but also insights about how the switch to EVs affected the mobility of single users. Our solution adds a novel perspective to the existing literature on the topic, the latter being mostly focused on the infrastructural issues, namely how to organize the energy distribution (e.g. where to place recharge stations) and how it will impact the current power grid, or on abstract path optimization problems, trying to minimize the battery consumption of trips or the overall time. Only a small portion of works try to quantitatively study how much the current mobility actually fits the constraints imposed by EVs, and in most cases that is done at a general level, e.g. counting the trips that might fit a given range [5] (with or without recharges) or studying the mobility characteristics of a territory to evaluate the sustainability of EV usage [6].

**The simulation framework.** In order to achieve our analytical objectives, we developed a framework made of two key components. The first one is an enriched road network obtained by integrating the basic OpenStreetMap network with elevation information and estimated battery consumption for each road segment, obtained through a mathematical estimation model, and with the availability of recharge stations at each node. The second one is a simulation process that takes as input the sequence of trips (origins and destinations) performed by a single user, and returns a simulated travel plan that mimics the original one adapting it to EV requirements. In turn, the process is based on two main functionalities: a fast heuristics for determining the best path to reach a destination starting with a given battery level, also performing intermediate stops (and associated deviation from the path) to recharge, when needed; and mechanisms for simulating passive recharges (i.e. performed while the vehicle was parked at a destination) at key places, such as the individual home or work, or nearby recharge stations. The concepts of home and work are automatically inferred from the input data, exploiting Individual Mobility Networks [7] (IMN).

In summary, the novel contributions of this paper are the following: (i) we develop an open source simulation framework [8] for EVs based on a set of (real) individual trips, that mirrors them according to EV constraints and battery recharge opportunities, including the availability of recharge at home and work; (ii) we define and implement fast heuristics to compute the best path from an origin to a destination, taking into account the battery constraints and, where needed, computing a deviation to reach a recharge station; (iii) we perform experimentation over a large dataset of real users in an Italian region, studying the impact of EVs on their mobility over various scenarios, both at the collective and individual levels; (iv) finally, we explore the impact of EVs on the mobility of a sample of users through a network (IMN) representation.

The paper is organized as follows. Section II discusses various angles of related works on EV data analysis and simulation. Section III defines the problem. Section IV describes the simulation framework and heuristics. Section V provides experimental results, and finally Section VI closes the paper.

## II. Related Works

Electric vehicles (EVs) are experiencing a rise in popularity over the past few years as the technology has matured and costs have declined. Support for clean transportation has promoted awareness, increased charging opportunities, and facilitated EV adoption. Suitably, a vast body of literature has been produced exploring various facets of EVs and their role in the transportation and energy systems.

### A. Studies on issues and opportunities of EVs

**Market and stakeholders studies.** Several papers and reports perform surveys to see how EVs fit individual needs [9], [10], mostly capturing the feelings of people or general statistics, thus not providing ways to profile the individual electrificability of users in objective terms. Vehicle price, fuel cost, driving range, battery replacement cost, charging time and maintenance cost are among the significant attributes considered in consumer choice modelling [11].

**Simulation-based studies.** Similar to our objectives, some studies on EVs make use of mobility data, typically to understand typical mobility needs of the population, and check how well they fit the main characteristics of EV mobility. E.g., in [6] general urban mobility behaviours in two Italian areas are studied through trip length, average speed and parking duration distributions, which are used to quantify the urban fleet share that can fit a switch to battery EVs. Also, [5] investigated the charging behaviour of EV drivers by simulating travels and charges at public chargers, showing that more than 5% of the trips would require recharging at a public charger for different driving range and charging assumptions. Some platforms allow running traffic simulations with all or partially electrified fleets, as in [12], where EVs are simulated in highway networks with online charging, and [13], where a spatial-temporal model is built based on a Poisson arrival location model (PALM) for EVs charging at public stations on the highway. *Compared to these works, our approach aims to analyze EVs' impact at a finer granularity, analyzing the single vehicle's mobility, providing more precise estimates and allowing a better understanding of the general phenomenon and of potential issues.*

### B. Simulating the EV mobility

In order to simulate the mobility of EV vehicles in a realistic and effective way, various factors should be taken into consideration.

**Route planning.** Identifying the best path from an origin to a destination in the context of EVs is a hard problem, since it adds constraints to the classical shortest-path task (namely, battery constraints) and requires finding trade-offs between travel time, energy consumption and time spent recharging. The problem can be formulated as a Constrained Shortest Path (CSP) task [14], and various approaches were studied to take into consideration different aspects: minimize overall travel and recharge time [15]; minimize energy consumption [16], also including battery capacity constraints and recharging road segments [17], as well as approximation schemas for the task [18]; find trade-offs between energy consumption and driving time [19]. *In our paper, we propose a greedy routing strategy that favours travel times (expected to be the priority criterion for average users) and plans recharge stops at stations in such a way as to minimize the combined cost of deviating the path and the recharge time.*

**Global optimization of EV mobility.** The several trips that make up a user's daily mobility clearly influence each other, as the battery recharges might be anticipated or postponed in various ways, in principle, calling for an overall optimization based on the knowledge of a long-term plan of movements. However, the state-of-the-art provided by routing software is currently based on Constrained Vehicle Routing solutions, such as OR-Tools [20], that typically require to precompute all shortest paths among the possible destinations, which is impractical for large-size simulations. *Our work* *provides fast-yet-accurate and reasonable heuristics, based on greedy single-step optimization, that reflects typical human behaviours and realistic situations. Since our aim is to achieve large-scale simulations, computational costs are critical.*

**Battery charge-discharge.** The authors of [21] consider that battery charging times are nonlinear using a particular cost function which takes this aspect into consideration. Indeed, while nearly linear for low state of charge, the charging rate decreases when arriving the battery limit. In [22] this aspect is modeled by matching a linear with an exponential function for high state of charge. At the same time, practical battery maintenance guidelines (e.g. [23]) suggest refraining from reaching such charge limits, thus linear charging can be assumed when operating within the devised charge ranges. *In our work we will adopt such a simplified model, although our framework can easily accommodate more complex ones. A practical effect of this is that (time-wise) there is no convenience to split a full battery recharge into in several small ones.*

**Mobility data analysis for EVs.** Mobility data analytics is a wide and active research field with applications in several domains, from driving behaviours to animal movement analysis, crowd dynamics, and so on. In particular, various tools have been developed to analyze individuals and extract their key movement characteristics. Among them, in [24] the notion of *mobility profile* is introduced, which summarizes the regular movements of a user. Such individual models are exploited in [25] for building an effective individual and collective movement predictor. The work in [7] provides a first definition of *Individual Mobility Networks* (IMNs), a network-based representation that integrates locations, movements, and their temporal dimension in a succinct way, allowing to infer semantic information of locations and trips, as well as simulating realistic mobility agendas [26]. *In our work we exploit IMNs to drive the overall simulation, identify key places (home and work) for defining the simulation scenarios, and, finally, to provide a more insightful analysis of results.*

## III. Problem definition

A simulation framework for EVs should aim to compute a mobility schedule that satisfies the (real) mobility demand $S_u$ of a user $u$ respecting the battery constraints of EVs and trying to minimize the overall cost that the user would experience in doing that. In particular, battery constraints require that the simulation identifies when and where recharges should take place. Also, the cost of a schedule might be defined in various alternative ways, such as the total time spent (probably the most natural choice, which will be adopted in our experiments), the amount of charge consumed, the overall distance travelled (considering that reaching a recharge station might require significant detours), and so on.

### A. Optimal EV schedule

We start by introducing the concept of EV schedule which is basically a sequence of stops including original mobility demand of the user and potential recharge stops that satisfies the basic requirements of EVs.

**Definition 1** ((Valid) EV-schedule)**.** *An* EV-schedule *is defined as a tuple $(S, c, r, b_1, b^*)$ composed of: a sequence $S = \langle s_1, \ldots, s_n \rangle$ of stop locations; a function $c : \{2, \ldots, n\} \rightarrow \mathcal{R}$ defining the amount $c(i)$ of battery consumed for traveling from $s_{i-1}$ to $s_i$ $(1 < i \leq n)$; a function $r : \{1, \ldots, n\} \rightarrow \mathcal{R}^+$ assigning the amount of battery recharged at each stop $s_i$; the initial battery level $b_1 \in \mathcal{R}^+$; and a maximum battery capacity $b^* \in \mathcal{R}^+$. The EV-schedule is said to be* valid *if the following holds:*

1) $\forall 1 \leq i \leq n : arrival\_batt(i) \geq 0$
2) $\forall 1 \leq i \leq n : arrival\_batt(i) + r(i) \leq b^*$

*where* $arrival\_batt(i) = b_1 + \sum_{j=1}^{i-1} r(j) - \sum_{j=2}^{i} c(j)$.

Constraints (1) and (2) above guarantee that the battery level is always maintained within practical limits at stops (0 to maximum capacity). We also observe that functions $c$ and $r$ basically define, respectively, the charge and discharge operations applied during the simulation.

**Definition 2** (Compatible EV schedule)**.** *Given the sequence $S_u$ of stops performed by a user $u$ and a set $R$ of recharge-enabled locations, we say that the EV-schedule $\xi = (S, c, r, b_1, b^*)$ is* compatible with $S_u$ and $R$ *(or simply* compatible*, when clear from the context) if:*

1) *$\xi$ is a valid schedule;*
2) *$S_u \sqsubseteq S$;*
3) *$\forall i.\ r(i) > 0 \iff s_i \in R$*

*with $\sqsubseteq$ denoting the subsequence relation.*

Finally, we introduce the general optimization problem:

**Definition 3** (Optimal EV schedule)**.** *An Optimal EV schedule for user $u$ is an EV schedule $\xi = (S, c, r, b_1, b^*)$ compatible with her sequence of stops $S_u$, such that it minimizes the total cost $C(\xi) = \sum \tau(i) + \sum \sigma(i)$, where $\tau(i)$ represents the cost of performing the trip between locations $s_{i-1}$ and $s_i$, and $\sigma(i)$ represents the cost of stopping/recharging at location $s_i$.*

### B. Instantiating the general problem definition

The definitions provided in the previous section can be instantiated in several different ways, depending on the factors that are considered more important to weigh for a specific context. We provide an instance of the general framework fitting the aim of this work, namely evaluating the potential impact of EV-based mobility over individual users' mobility. We do that by defining the parameters and functions involved in the definitions above, namely $c(i)$, $r(i)$, $\tau(i)$ and $\sigma(i)$:

**Definition 4** (EV Time Minimization Problem)**.** *Given a user $u$, the* EV time minimization problem *consists in finding an optimal EV schedule for $u$ under the following definitions:*

- *Battery consumption $\boldsymbol{c(i)}$ is computed assuming to follow the fastest path between the two locations $s_{i-1}$ and $s_i$. Also, since roads can have a negative battery consumption (recharging when traveling downhill) we ensure that the battery level never exceeds the cap $b^*$.*
- *Recharge amount $\boldsymbol{r(i)}$ is defined in two different cases: if the visited location was already in the original schedule, then the recharge lasts exactly the stop duration; in any*

*other stop, it lasts as much as needed to fill the battery up to the cap. Also, we assume that the recharge speed remains constant for a given station, regardless of the current battery level, which is an approximation.*

- *Trip cost $\tau(i)$ is computed as the travel time between locations, not considering other parameters at this stage, such as battery consumption.*
- *Recharge cost $\sigma(i)$ is computed as time spent recharging if the recharge happens in a new stop introduced in the EV-schedule, and zero in the other cases (what we call also passive recharges). Recharge time is assumed to be linear in the amount of energy required, while queue waiting times at stations are not considered.*

Our final objective is then to evaluate the cost of an optimal EV schedule under time minimization as compared to that of its original, internal combustion engine-based one.

### C. The four simulation scenarios

A fundamental aspect that affects EV mobility is the availability of recharge options. Part of them is determined by the public infrastructures on the territory, which are basically the same for every user. Others depend on the user's status, which therefore might in principle condition their capability of safely replacing the current internal combustion engine (ICE) vehicle with an electric one. We consider the following four basic settings, covering a range of different recharge opportunities.

**Public Station Scenario**. The user can only recharge the battery at public stations. This represents the worst-case scenario, as no other recharge options are available. We remark that, according to Definition 4, if the stop at a recharge station was already in the original schedule (i.e. the user was visiting that area for purposes unrelated to the station itself) then the recharge is not considered as a cost. The recharge takes place only if the stay lasts at least a given minimum duration, that we set at 1 hour as default, and is interrupted when the stay ends (i.e. the battery might be only partially recharged).

**Home Scenario**. The user can recharge on public stations when needed (thus making deviations for the actual trip and wasting time while waiting for the recharge), and also at home every time they stop there for at least a specific minimum duration, our default threshold being 20 minutes.

**Work Scenario**. Similarly to the Home Scenario, the user can recharge at their work location when they stop there for at least a minimum duration, the default threshold being 20 minutes.

**Home And Work Scenario**. Both Home and Work options are available. Clearly, this is the best scenario for the user, since there are more opportunities for recharging without spending time reaching stations and waiting.

**Emergency Situations**. In addition to the scenarios above, we define a specific situation: when the initial battery at a starting location is not sufficient to reach the destination or any charging station, the user runs into an emergency situation. These cases will be counted separately, representing a critical measure of the usability of EVs. In terms of simulation, we assume that in case of emergencies, the vehicle is rescued and transported to destination, where it can continue the schedule with a fully-recharged battery.

According to literature, the share of users belonging to each scenario is quite variable from country to country, yet typically showing a majority in the Home and Home-and-Work ones. From EU estimates [27] it follows that 33% can recharge at home, 11% at work, 44% in both, and just 12% only at public stations; also, these statistics fit with information available for Italy (e.g. [28] cites 80% of EV recharges performed at home) and other countries (e.g. Canada [29].)

## IV. Simulation Framework

### A. Setting the stage: battery charging/discharging on the map

*Battery consumption model:* Our estimation of battery consumption for each trip of the user is based on an instantaneous consumption model introduced in [30] and recommended in [31] as a good trade-off between realistic simulation and efficient computability. The model considers all the physical forces to which the vehicle is constantly exposed in order to estimate the amount of electric power needed to reach a certain speed, and includes rolling resistance (based on tire characteristics), mass of vehicle and driver, slope of the road, aerodynamic resistance, air density and vehicle speed. Also, the efficiency of the vehicle, such as engine and gear efficiency, and the energy consumption due to onboard electronics are estimated. Finally, regenerative breaking is considered, recovering a fraction of the energy lost during decelerations. In our simulations, we will consider a medium-class car model, with associated parameters. In particular, we will fix the maximum battery capacity to 40 kWh, which represents a lower-end setting. More details, including all the physical parameters adopted, are given in the Appendix (Section A).

*Estimating elevation and speed:* Our basic source of geographical information is OpenStreetMap (OSM), which provides a road network graph. Then, we imputed the maximum travel speed on each road, the altitude of the nodes, and subsequently, the slopes of the respective edges.

**Speed.** Since OSM typically does not provide complete information about speed limits (only 10% of road segments in our area of study had it), we estimate it through the road type information (the *Highway* attribute), which is always available and distinguishes among alleys, crossings, motorways, residential, etc. Each type was then associated with its most common speed limit adopted in the area.

**Slopes.** We deploy the Copernicus DEM open data, of the European Space Agency, to assign the elevation information of each node in the road network, then the slope of each edge is computed as its average variation.

*Estimating road-level discharge:* In computing the battery consumption on one edge (road), the speed and the slope on the edge were assumed constant and the maximum speed limit for that edge was chosen as speed. Finally, the consumption by the vehicle on the edge was calculated, based on the battery consumption model described in the previous section.

*Integrating public recharge stations:* Finally, we extracted from the popular public repository OpenChargeMap the list of recharge stations available in our area of interest, associated each of them with the closest node of our road network (thus labelled as *public recharge location*) and with its maximum recharge power available.

### B. EV-compliant best path computation

*Best path heuristics:* As described in Section III-B, the path selected to reach a destination is simply the fastest one, when the battery constraints allow that. When that is not possible, an intermediate stop at a reachable charging station is performed, selecting the one that minimizes the overall time (travel for the new path plus recharge time). In order to add flexibility to the schema, we compute the overall time as a weighted sum of its three components:

$$k_1 \cdot t_{orig \to station} + k_{charge} \cdot t_{recharge} + k_2 \cdot t_{station \to dest}$$

That allows us to model various contexts, for instance, favouring short recharge times at the cost of longer trips (increase $k_{charge}$) or postponing recharges ($k_1 < k_2$). In complex situations, especially with long trips, one stop might be insufficient, thus requiring a multi-stop optimization that might greatly increase computation times. Our approach to the problem is a greedy solution that identifies the first recharge stop assuming that one stop is sufficient to reach the destination; then, if that is not the case, we repeat the same process to reach the destination from the current station (now starting with a full battery), thus greedily identifying the next stop, as above.

*Paths precomputation:* Our simulation technique relies heavily on shortest-path computations. To improve the simulation performance, we perform offline shortest path precomputations to collect some useful information. However, considering the quadratic space requirements of storing the shortest paths of all node pairs in the road network graph, we limit the precomputations to/from charging station nodes and store only the aggregate information about paths. We achieve that by using Dijkstra's algorithm [32], adopting the edge traversal times as weights.

We denote with $\mathcal{P}(n_i, n_j)$ the precomputed shortest path between nodes $n_i$ and $n_j$. For each pair of nodes, we store aggregate information about the shortest path's total traversal time $\mathcal{P}^{time}_{tot}(n_i, n_j)$, spatial length $\mathcal{P}^{length}_{tot}(n_i, n_j)$, and consumption $\mathcal{P}^{cons}_{tot}(n_i, n_j)$. This information is not always sufficient to infer the final battery level of the vehicle after traversing a path, since it can contain recharge edges (downhill roads) that might either take the battery level beyond the maximum capacity or hide a peak of consumption within the path. For instance, the sequence of edge consumptions (and recharges, when negative) $\langle -2, 3, 5, -3 \rangle$ yields a total consumption $\mathcal{P}^{cons}_{tot}(n_i, n_j) = 3$, yet, if the initial charge level is very close to the maximum capacity, the passive recharge provided in the first leg ($-2$) would be wasted, since the battery cannot store it, and the effective final consumption would be 5, i.e. higher. At the same time, starting with a charge level slightly larger than the consumption does not guarantee to reach the destination. Indeed, in the example above, the first three legs of the path reach a total consumption of $-2+3+5 = 6$, thus if the initial charge level of the vehicle is 4, it would run out of energy at the third leg. To account for this dynamic behavior, we store two additional values for each path: the *maximum charge* $\mathcal{P}^{charge}_{max}(n_i, n_j)$ which indicates an upper bound for the battery level of the vehicle that guarantees the battery will not go beyond the capacity considering all the downhill recharges along the path; and the *minimum charge* $\mathcal{P}^{charge}_{min}(n_i, n_j)$, which is the minimum initial charge needed for the vehicle to safely reach $n_j$.

Algorithm findMinMaxCharge summarizes the computation of $\mathcal{P}^{charge}_{min}$ and $\mathcal{P}^{charge}_{max}$ for a sequence of path consumptions $consSeq$ and a maximum battery capacity $C$, following the intuition given through the example above. In line 1, we first compute the sequence of prefix sums of $consSeq$. The prefix sum indicates the vehicle's battery levels, starting with a battery level of zero from the first edge of the path.

**Function** findMinMaxCharge

**Input :** consumption sequence *consSeq*, and battery capacity $C$
**Output:** (*minInitCharge*, *maxInitCharge*)

```
1 prefixSumSeq ← compute prefix sum of consSeq
2 minInitCharge ← max (prefixSumSeq)
3 maxInitCharge ← C
4 if min (prefixSumSeq) < 0 then
5 |   maxInitCharge ← C + min (prefixSumSeq)
6 return (minInitCharge, maxInitCharge)
```

The maximum prefix sum of $consSeq$ specifies the minimum amount of charge needed for the vehicle to follow the path successfully. On the other hand, if the minimum of this prefix sum sequence denoted by $ps_{min}$ is negative, then the path has a subsequence that charges the battery. Thus, if the vehicle arrives at that edge with a charge of $C$, no recharge will happen as the battery is already full. Thus, in that case, the upper bound of the battery level to avoid exceeding the battery limit is $C + ps_{min}$ (line 4). However, if $ps_{min}$ is positive, we can infer that the upper bound would be the battery's capacity (line 3). The correctness of Algorithm findMinMaxCharge and its usage are formalized by the following:

**Property 1.** *Given a path having prefixSumSeq, minInitCharge and maxInitCharge as defined in Function findMinMaxCharge, we have that:*

- *if the initial charge $c$ is such that $c < minInitCharge$, then the path is not doable by the vehicle;*
- *if $minInitCharge \leq c \leq maxInitCharge$, then the path is doable, and the final charge is $c - prefixSumSeq$;*
- *if $c > maxInitCharge$, then the path is doable, and the final charge is $maxInitCharge - prefixSumSeq$.*

*Proof.* If $minInitCharge \leq c \leq maxInitCharge$, then the battery level $c(t)$ remains within the interval $[0, C]$ throughout the path with no battery overflows nor empty battery issues, thus the final level will simply be $c(t_{final}) = c - prefixSumSeq$. Assuming that $c < maxInitCharge$ (and thus there are no overflows), if $c < minInitCharge$ there is a time $t^*$ in the path where the battery goes below zero ($c(t^*) < 0$), and thus the path is not doable. It is easy to see that if $c > maxInitCharge$ then the battery levels $c'(t)$ obtained at each time $t$ are such that $\forall t : c'(t) \leq c(t)$, and thus also in this case $c < maxInitCharge \Rightarrow c(t^*) < 0$ and the path is not doable. Finally, if $c > maxInitCharge$ there is at least a time $t^\top$ where $c(t^\top) > C$ and the battery level is capped to $C$ and thus the battery levels from this point on will be exactly the same we would obtain (with no overflows) when $c = maxInitCharge$, hence $c(t_{final}) = maxInitCharge - prefixSumSeq$ by applying the formula of the first case. □

The precomputation of shortest paths is justified mainly by the fact that road networks and charging stations in the network do not change frequently, and the precomputation can be done offline when significant changes happen to the network.

### C. User history EV-simulation

Algorithm 1 summarizes our proposed procedure for the overall simulation of EV users' mobility. The procedure is based on the general simulation parameters listed in Table I, which are all passed to Algorithm 1. In addition, the algorithm receives the road network graph $G$ and the sequence of a user's trajectories $\mathcal{T}$ sorted chronologically. Also, two parameters indicating the nodes where the user can recharge at home or at work, set to *null* if home/work recharge is not allowed.

The simulation starts using the origin and destination of each trip in user's history $\mathcal{T}$ to simulate the sequence of consecutive locations that the user intends to visit. Hence, the graph nodes $orig$, $dest$ that correspond to the origin and destination of the trip are obtained (line 4). The duration of user's stay at $orig$, which is basically the time they spent from the end of the previous trip until the start of the current trip, is computed in line 5. If the home or work recharges are allowed, and the user stays there for at least a predefined amount of time $ms$, a home or work recharge is done before the next trip starts from $orig$ (lines 6-9). The same applies to stays longer than $mdms$ at locations corresponding to a station (line 11).

Next, lines 14-19 compute a shortest path from $orig$ to $dest$ using the edge traversal time as weight criterion. If the shortest path is feasible given its sequence of edge consumptions, then $reached$ is set to $True$ and both $orig$ and $dest$ are inserted into the simulated path sequence $\mathcal{S}$. Otherwise, depending on the current battery level $cc$, a list of reachable charging stations is fetched from the precomputed information $\mathcal{P}$ (line 21). Note that, there might be no reachable charging stations if the battery level of the vehicle is too low, in which case, the current trip simulation is interrupted (lines 22-23).

Then, the best charging station $recharger$ is selected among the possible options using the heuristics described in section IV-B (line 25). According to Property 1, if the current charge of the vehicle is lower than $\mathcal{P}^{charge}_{max}(orig, recharger)$, then the vehicle will consume the energy equal to the sum of path's edge consumptions. Otherwise, the same computation will be performed, yet capping the initial battery level at $\mathcal{P}^{charge}_{max}(orig, recharger)$ (lines 26-29). Then, a recharge is done at $recharge$ (line 30), the number of recharges for the current origin/destination pair is incremented (line 31), the node $orig$ is added to $\mathcal{S}$ and $recharger$ is set as the origin node for the next trial in reaching the destination (lines 32-33). This process repeats until either the vehicle reaches the destination or the number of recharges exceeds the $maxRecharges$ threshold. In case it is not possible to reach the destination, the algorithm raises an emergency condition and continues with simulating the next trip (lines 34-36).

**Algorithm 1:** (EV Strategy)

**Input :** $G$, $\mathcal{T}$, $homeNode$, $workNode$ and General Parameters (Table I)
**Output:** Simulated Path $\mathcal{S}$

1 $\mathcal{S} \leftarrow \langle\rangle$
2 $cc \leftarrow b_1$ `// cc is the current charge`
3 **foreach** $t \in \mathcal{T}$ **do**
4   $orig, dest \leftarrow G.getNode(t.s), G.getNode(t.e)$
5   $stayDur \leftarrow$ stay duration at $orig$ before starting $t$
6   **if** *homeNode* $\neq$ *null* ***and*** $orig == homeNode$ ***and*** $stayDur \geq ms$ **then**
7     $cc \leftarrow$ recharge at home
8   **else if** *workNode* $\neq$ *null* ***and*** $orig == workNode$ ***and*** $stayDur \geq ms$ **then**
9     $cc \leftarrow$ recharge at work
10   **else if** *orig has a station* ***and*** $stayDur \geq mdms$ **then**
11     $cc \leftarrow$ recharge at station
12   $reached \leftarrow False$;  $rechargeCount \leftarrow 0$
13   **while** ***not*** *reached* ***and*** $rechargeCount \leq maxRecharges$ **do**
14     $p \leftarrow SP(G, orig, dest, weight =$'traveltime'$)$
15     $consSeq \leftarrow$ consumptions of $p$'s edges
16     $(isFeasible, cc) \leftarrow$ `isFeasible`(*consSeq, batCap, cc*)
17     **if** *isFeasible* **then**
18       $reached \leftarrow True$; $\mathcal{S}$`.insert`(*orig*); $\mathcal{S}$`.insert`(*dest*)
19       break
20     **else**
21       $rcs \leftarrow \{\text{stations } cs \mid cc \geq \mathcal{P}^{charge}_{min}(orig, cs)\}$
22       **if** $rcs = \emptyset$ **then**
23         break
24       $recharger \leftarrow \arg\min_{s \in rcs} \; k_1 \cdot \mathcal{P}^{time}_{tot}(orig, s) \; + \; k_2 \cdot \mathcal{P}^{time}_{tot}(s, dest) +$
25         $+ \; k_c \cdot recharge\_time(s)$
26       **if** $cc < \mathcal{P}^{charge}_{max}(orig, recharger)$ **then**
27         $cc \leftarrow cc - \mathcal{P}^{cons}_{tot}(orig, recharger)$
28       **else**
29         $cc \leftarrow \mathcal{P}^{charge}_{max}(orig, recharger) - \mathcal{P}^{cons}_{tot}(orig, recharger)$
30       $cc \leftarrow b^*$ (full recharge and collect statistics)
31       $rechargeCount \leftarrow rechargeCount + 1$
32       $\mathcal{S}$`.insert`(*orig*)
33       $orig \leftarrow recharger$
34     **if** ***not*** *reached* **then**
35       EMERGENCY condition
36       $cc \leftarrow b^*$
37 **return** $\mathcal{S}$

## V. Experiments

### A. Setting up the stage

In this section, we describe the dataset used and the general setting of the experiments carried out. Also, some properties of the dataset are explored, to give the reader a better understanding of the application context.

*Dataset:* Our experiments are based on a proprietary dataset of real GPS traces from 1000 private vehicles moving in the Tuscany region, Italy, and spanning 2 months in March and April 2017. The vehicles represent residents from (i.e. their main location belongs to) five provinces (Arezzo, Firenze, Lucca, Pisa, and Pistoia), although their trips can span all over the region. The raw data is segmented by identifying *stops*, defined as points where a vehicle remains within a

TABLE I
GENERAL SIMULATION PARAMETERS

| Parameter | Description | Default |
|---|---|---|
| $k_1$ | Weight of the first leg of the path (origin→recharger) | 0.4 |
| $k_c$ | Weight for time to fully recharge the battery at the station | 0.2 |
| $k_2$ | Weight of the second leg of path (recharger→destination) | 0.4 |
| $ms$ | Min stay duration threshold for charging | 20 mins |
| $mdms$ | Min stay duration threshold to charge in nearby station | 60 mins |
| $maxRecharges$ | Maximum number of recharges allowed during a single trip | 3 |
| $b^*$ | Battery capacity | 40 kWh |
| $b_1$ | Initial charge | $b^*$ |
| $\mathcal{P}$ | precomputed data | N/A |

distance of 50 meters for at least 20 minutes. Each trip is then represented by its pair of origin and destination points, filtering out trips shorter than 1 km (typically representing cases where the vehicle is simply parked in a different slot in the same area). This results in a total of 176,300 trips. In order to make the results of our simulation perfectly comparable with the real mobility data, the trip between each origin and destination pair is reconstructed through a fastest path heuristics – the same used in the simulation, yet with no battery constraints –, storing its length and duration. This reduces the impact of imperfections in the road network (missing edges, incorrect speed, etc.) over the comparison process. Each origin and destination point is snapped to the closest node in the road network, and we use the shortest path function provided by the NetworkX library [33] using traversal time as edge costs.

*Home and Work:* In order to implement the simulation scenarios it is essential to identify the locations representing home and work places. We do that following the approach described in [7], [34], [35], which infers a graph structure of the user's mobility named *Individual Mobility Network* (IMN), and identifies visited locations and their frequency. The first and second most frequently visited locations are then selected, resp. as home and work place of the user.

*Dataset statistics:* As shown in Figure 1, most users have more than 100 trips in the observation period and an average number of trips per day ranging from 2 to 8, suggesting that the movement history of the users analyzed is significant.

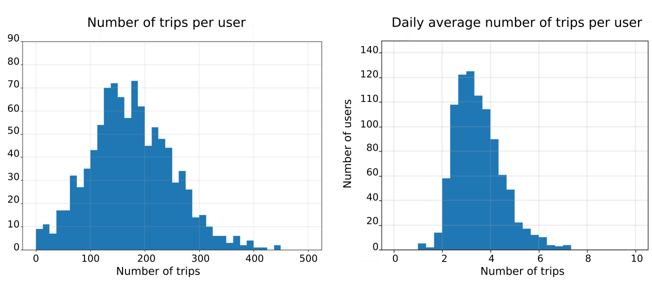


Fig. 1. *Distribution of the number of trips involved in the experiments: (left) trips per user; (right) trips per day of each user.*

The length of the trips is studied in Figure 2(left), and shows a log-normal shape, representing the fact that there are many trips of medium-short length (less than 10km, in most cases), as well as a significant number of moderately long ones (between 10km and 40km) and a small fraction of long trips (longer than 40km up to 300km), which appears to be coherent with the extension of the geographical area considered. Figure 2(right) compares duration and length of the trips, showing a linear relation, as expected, with a variability that grows with the trip length. Longer trips, belonging to the tail beyond 100km, appear to have a more stable average speed (around 100 km/h), probably due to the fact that they are mostly performed along high-speed roads.

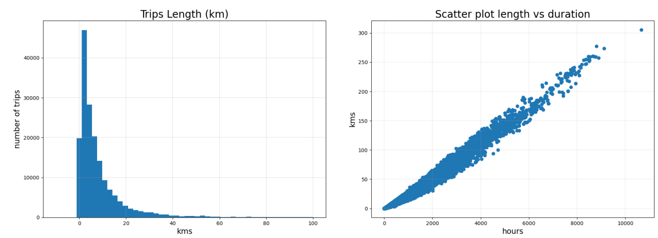


Fig. 2. *Distribution of trip lengths (left) and duration (right).*

The experiments make use of two sources of geographical data: OpenStreetMap, for the road network of Tuscany, which is composed of 138792 nodes (intersections) and 305804 edges (road segments); and OpenChargeMap, for the catalogue of recharge stations available on the territory and their power, for a total of 354 stations. Figure 3 shows the distribution of recharge power and the geographical disposition of stations. Recharge stations are grouped by power category, following the current standard classification (see, e.g., [36]): *slow* if $power < 7kW$, *fast* if $7 \leq power < 25kW$, *rapid* if $25 \leq power < 100kW$, *ultra-rapid* if $power > 100kW$. The most common ones are fast rechargers (78%), especially with a power of 22 kW, although there is a good number of rapid ones (8%), and a few ultra-rapid (1.7%). Around 55% of stations provide 2 plugs, 13% only one and 24% 3-4 plugs, while the remaining 8% go up to 38. The large majority of stations are in the Northern part of Tuscany, in particular along the line connecting Florence and Pisa.

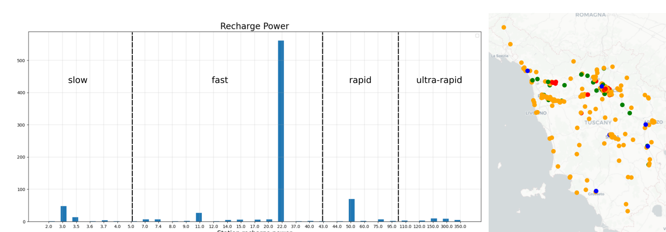


Fig. 3. *(left) Number of stations by maximum recharge power provided (in KW); (right) Geographical distribution of stations (red=slow, orange=fast, green=rapid, blue=ultra-rapid). Original map created from OCM data.*

## B. *Runtime evaluation*

As mentioned above, we aim to run our simulations on large pools of vehicles and long time periods. For this reason, in this section we will evaluate the scalability of the proposed approach w.r.t. the input dataset size (namely the number of trips involved in the simulation) and its complexity (namely the length of trips). We consider the two extreme scenarios: public-only recharges and recharging also at home and work.

Figure 4 shows the growth of runtimes for increasing sizes of the input dataset. In particular, each data sample is composed of the first $N$ trips in chronological order, and the ticks in the plot at every 20k trips also correspond approximately to one more week of data. Runtimes grow linearly in the input size for both scenarios, as we could expect given that each trip is only loosely dependent on the previous ones, with times ranging from $\sim$200 seconds (for 10k trips) to $\sim$4000 seconds (160k trips). Also, the public-only scenario has slightly higher runtimes due to its higher chances of deviations to recharge stations, which add complexity to the process and increase runtimes. Notice that these time measures do not consider the fixed cost of the pre-computation phase described in Section IV-B, which depends only on the geographical area of interest and not on the mobility data. In our experiments, pre-computations added an amortized cost equivalent to $\sim$221 milliseconds per trip, assuming to amortize it over a single simulation run (i.e. a single scenario with a single set of parameters). While still significant, it easily becomes negligible when multiple runs are needed (as for the set of experiments in this paper) or larger datasets are employed.

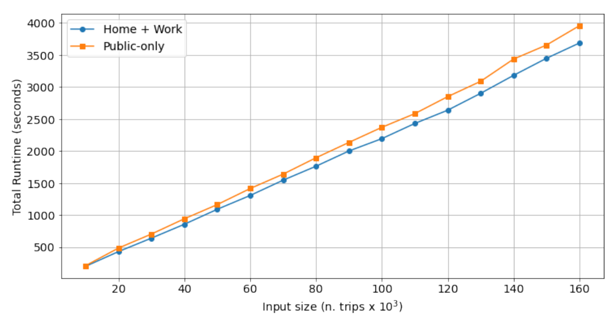


Fig. 4. Simulation runtime for different input sizes (seconds vs. n. of trips).

Simulating short trips is expected to be less expensive than longer ones, since the latter usually involve a more complex shortest path computation and there are also higher chances that an additional stop at a recharge station needs to be planned. The plots in Figure 5 shows how runtimes increase with the trip length, both in the Home and Work scenario (top plot) and in the Public-only one (bottom plot). Results follow an approx. linear growth with the trip length, and the vast majority of trips (more exactly, 96.9%) are less than 30 km, for which the single trip cost is virtually always less than 50 milliseconds. The main difference between the two scenarios is the variability of runtimes, which appears to be slightly higher for the public-only one.

As mentioned in the related works, most competing approaches available in literature aim to precisely optimize the single trip, yet require much higher computational costs – indeed, the optimal routing algorithm behind them (e.g. [37]) is known to be $\mathcal{NP}$-hard, and thus hardly applicable to large and medium-sized setting as the one we are considering here, which requires to simulate more than 170k trips over a road network composed by over 300k edges. Our heuristics, instead, results to be efficient enough to run each experiment in around 1.2 hours on a single commodity machine.

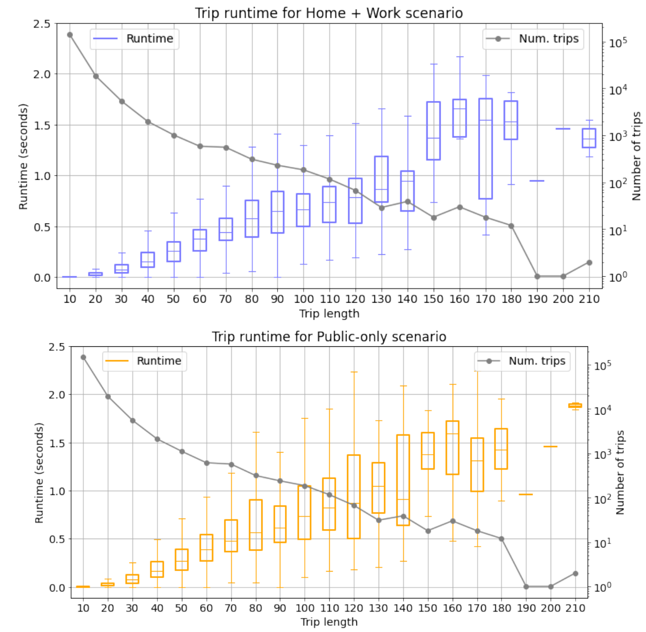


Fig. 5. Average runtime for trips, divided by trip length, for the Home and Work scenario (top) and the Public-only one (bottom). The black line represents the number of trips in each group (log-scale).

## C. *Simulation results*

*Overall impact of EV on individual mobility:* The core of the experiments consists of a comparison of the original trips against the simulated ones on the four scenarios (charge at public stations only; public and home; public and work place; public and home + work) over the whole dataset. In addition, we created 100 random *sample mixes* of the four scenarios, associating each user to one of them by following the representative distribution statistics for (some) EU countries provided in [27], according to which 77% of users can recharge at home, 55% at work and 12% in none of them. The results are summarized in Table II. First, we can see that the average lengths of the trips in the four scenarios are very similar to the original ones, with an increase of less than 1%, signifying that deviations for recharging are on average modest. In terms of trip duration, the worst-case scenario yields increments that are moderate in absolute terms (+1'17") and yet, given the typical short lengths of trips, are significant in relative terms, reaching a 18.11%. This percentage very quickly drops to moderate levels when recharge-at-work is introduced, and to modest ones with recharge-at-home.

The simulations yield a 0.75% of emergencies in the public-only scenario, which is relatively large. We believe this to be an overestimate of real user issues, mainly caused by the insufficient distribution of recharge stations in Tuscany (currently covering only larger cities and main ways), aggravated by the incompleteness of OpenChargeMap (we estimate it is missing $\tilde{3}0\%$ stations). With the growth of the EV infrastructures, we expect that these factors will be greatly alleviated in the near future. Introducing other recharge options drastically reduces emergencies down to 0.03% for the home + work case. Similar results are obtained for the percentage of trips with recharges

TABLE II

*Overall impact of EVs on trips. We focus on the comparison between the average length and the average duration of real and simulated trips.*

| Scenario | | Avg. length (km) REAL | EV | DELTA | Avg. duration (s) REAL | EV | DELTA | Emergencies | Recharges |
|---|---|---|---|---|---|---|---|---|---|
| public-only | | 9.323 | 9.415 | +0.98 % | 7'9" | 8'26" | +18.11 % | 1270 (0.72%) | 2.26 % |
| work | | | 9.358 | +0.37 % | | 7'36" | +6.29 % | 328 (0.19%) | 0.95 % |
| home | | | 9.337 | +0.15 % | | 7'18" | +2.06 % | 94 (0.05%) | 0.41 % |
| home + work | | | 9.334 | +0.12 % | | 7'16" | +1.79 % | 60 (0.03%) | 0.34 % |
| sample mix | avg | | 9.347 | +0.26 % | | 7'27" | +4.34 % | 246 (0.14%) | 0.66 % |
| | std | | ±0.00 | ±0.02 % | | ±0'1" | ±0.22 % | ±15 (±0.01%) | ±0.02 % |

TABLE III

*Temporal variations of EVs impact for the four scenarios. The two-month period is split into four shorter periods of two weeks each ($t_1$, $t_2$, $t_3$ and $t_4$) in order to see how the percentages change inside the selected time.*

| | **Increment Length %** | | | | **Increment Time %** | | | | **% Recharge Trips** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $t_1$ | $t_2$ | $t_3$ | $t_4$ | $t_1$ | $t_2$ | $t_3$ | $t_4$ | $t_1$ | $t_2$ | $t_3$ | $t_4$ |
| **public-only** | 0.68 | 0.99 | 1.04 | 1.19 | 12.24 | 18.82 | 19.5 | 20.8 | 1.61 | 2.25 | 2.3 | 2.77 |
| **work** | 0.3 | 0.36 | 0.35 | 0.42 | 4.77 | 6.67 | 5.89 | 7.64 | 0.7 | 0.94 | 0.9 | 1.23 |
| **home** | 0.08 | 0.18 | 0.13 | 0.23 | 1.49 | 1.79 | 1.82 | 3.12 | 0.31 | 0.37 | 0.36 | 0.59 |
| **home/work** | 0.05 | 0.12 | 0.1 | 0.19 | 1.33 | 1.52 | 1.59 | 2.73 | 0.26 | 0.3 | 0.3 | 0.5 |

TABLE IV

*Geographical variations of EVs impact. Each province is associated to the trips that start from it.*

| | **Increment Length %** | | | | | **Increment Time %** | | | | | **% Recharge Trips** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Arezzo | Florence | Lucca | Pisa | Pistoia | Arezzo | Florence | Lucca | Pisa | Pistoia | Arezzo | Florence | Lucca | Pisa | Pistoia |
| **public-only** | 1.0 | 1.13 | 0.96 | 0.55 | 0.93 | 14.3 | 22.2 | 17.0 | 13.6 | 19.6 | 1.5 | 2.59 | 1.96 | 2.04 | 1.9 |
| **work** | 0.21 | 0.4 | 0.38 | 0.14 | 0.26 | 3.35 | 7.21 | 4.81 | 3.99 | 5.76 | 0.47 | 1.05 | 0.76 | 0.67 | 0.65 |
| **home** | 0.03 | 0.1 | 0.09 | 0.04 | 0.03 | 0.42 | 0.92 | 0.87 | 0.96 | 1.0 | 0.1 | 0.28 | 0.21 | 0.24 | 0.15 |
| **home/work** | 0.02 | 0.06 | 0.05 | -0.01 | 0.01 | 0.27 | 0.71 | 0.62 | 0.52 | 0.5 | 0.07 | 0.21 | 0.16 | 0.13 | 0.08 |

at stations. Finally, we observe that the representative sample mix achieves rather low values, that are between the recharge-at-work and the recharge-at-home scenarios.

Overall, the results show that by applying the simple charge management heuristics considered in this paper, the majority of trips incur minor deviations from the original ones. Considering the sparseness of the current recharge infrastructures available in the area of study, that provides positive feedback for individual users about the feasibility of switching to an EV without changing any aspect of their mobility habits.

These results can be seen from the perspective of the single individual, in order to understand if the moderate average impact measures shown actually hide smaller portions of largely affected users. Figure 6 represents the distribution of the duration increase (left) and distance increase (right) measured by aggregating times and distances by the user. As we can see, the figure not only confirms that introducing home/work as recharge opportunities the impact is reduced (the peak around a 0 increase grows significantly), but also that virtually no user suffers increases above 4% in any of the scenarios.

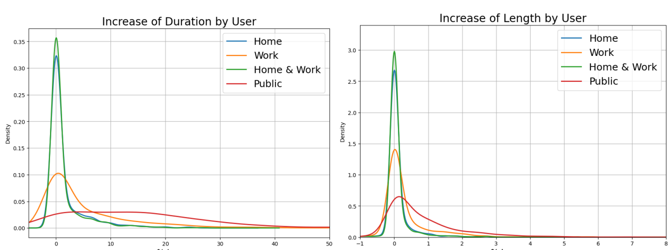


Fig. 6. Distribution of increase of trip duration and length aggregated by user.

*Temporal stability of results:* In order to evaluate if the results obtained are time-dependent, we provide in Table III aggregates over four consecutive bi-weeks for the four scenarios. We can observe that there is indeed some variability, and also a general slight increase on all measures considered, yet always remaining at low levels and well below 1%. The increase can be justified by considering that some vehicles travel relatively little, and thus it is unlikely that they will need recharging during the first bi-weeks, concentrating recharges (and, consequently, deviations) later in the period.

*Spatial stability of results:* Since our dataset spans a significantly large area, and the recharge infrastructures are not homogeneously distributed, we try to understand if trips in different provinces suffer from deviations of different intensities. Table IV summarizes the results. Here we can see that, indeed, different areas show a different impact level. In particular, Pisa benefits from a larger number and better distribution of recharge stations at least in relation to its size, and thus shows a significantly smaller impact than the others. Firenze and Lucca have similar values that are much larger than Pisa, most likely because of the large extension of Firenze, resulting in a lower density of stations, and the limited number of stations in Lucca, only partially balanced by the proximity to Pisa and its infrastructures. Finally, Arezzo and Pistoia are less covered by stations and also slightly peripheral to the other big cities. As a final remark, we notice that the impacts of the single provinces are smaller than the aggregates shown in Table II. This is due to the fact that trips originating outside provinces are not included here, and they indeed tend to be longer and traverse less populated (also in terms of stations) areas.

*Impact of heuristics' parameters:* When a direct trip to a given destination is not possible because of a battery charge shortage, the proposed heuristics builds a path passing through a reachable recharge station, which is chosen by considering the travel time to reach the station, the travel time to reach the destination from the station, and the recharge time. The weight associated to each component is defined, respectively, by parameters $k_1$, $k_2$ and $k_{charge}$. In this paragraph we discuss the effects of different choices of parameters, in terms of performances and also in terms of station usage.

Since stations can have very different recharge speeds, it can happen that the heuristics chooses to perform large deviations (and thus spend more time to travel) in order to reach a fast recharger and thus spend less time recharging. For this reason, high values of $k_{charge}$ are expected to increase the usage of the highest speed stations. Figure 7 shows the distribution of recharges on the different station types, grouped by power/speed, for different values of $k_{charge}$. As we can see, when the weight of recharge time is null, recharges are strongly concentrated on relatively slow stations, namely those labeled as "fast", which are the most popular on the territory. With $k_{charge} = 0.2$ the distribution immediately changes, and the peak is now on the "rapid" group. Further increasing $k_{charge}$ has little effect on the slow/fast group, whereas the

TABLE V

RESULTS OF COMPARISON OF OUR SYSTEM AGAINST ABRP.

| | $\Delta$ recharge amount | $\Delta$ recharge time | $\Delta$ distance | $\Delta$ travel time |
|---|---|---|---|---|
| Average | -13.4% | -24.6% | -2.0% | -35.3% |
| Median | -15.8% | -35.6% | -2.9% | -36.7% |
| Min | -24.8% | -86.1% | -28.6% | -59.6% |
| Max | 5.6% | 79.5% | 40.8% | 1.8% |

rapid one slightly decreases in favour of the "ultra-rapid". In all cases, the slowest stations in the "fast" category and those in the "slow" one have a marginal role, since they are not common enough nor convenient in terms of recharge time.

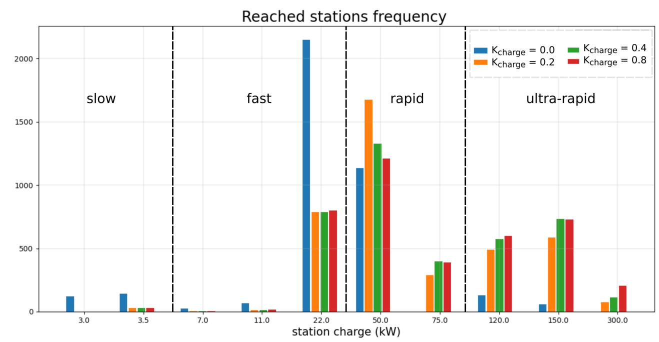


Fig. 7. *Usage frequency of stations by power by increasing values of $k_{charge}$ (weight of recharge time in the path selection algorithm).*

Table VI describes how the impact of EVs changes when varying the travel time parameters ($k_1$ and $k_2$). Increasing $k_2$ has no clear effect on the length and duration of trips, while it apparently leads to a slight reduction in the number of recharges required. This might be motivated by the fact that high values of $k_2$ promote recharges that are closer to the final destination, which is thus reached with more charge in the battery for the following trips. A low $k_2$, instead, would favor early stops at stations along the trips, resulting in lower battery levels at the destination.

*Validation of results:* In order to test whether our solution provides results coherent with other existing EV-related services, we compared it against the popular online EV-based trip planner ABRP (https://abetterrouteplanner.com/) through a small-scale experiment covering 20 users over one day.

The comparison was performed as follows. A random selection of 20 users was done, then for each of them one day was chosen having a significant number of trips. In particular, we selected 10 days/users that required at least one recharge in our simulation, and 10 others that did not. Each day containing $n$ trips was inputted to ABRP as a single trip with $n-1$ intermediate stops, requiring that the start battery level was the same as the first trip in our simulated day, and the final battery level to be the same as that obtained from our simulation.

Results, reported in Table show that the trips generated by ABRP have a similar length (average difference around 2%) and a significant, yet stable increase in driving time (35.3%) and recharging time (24.6%, computed only on the 10 days with recharges) – which can be attributed to ABRP referring to real-time, and thus traffic-affected, road status information

TABLE VI

*Effects of varying $k_1$ and $k_2$ on EVs impact. $k_{charge}$ is fixed to 0.2.*

| Parameters | | **% Increment Length** | **% Increment Time** | **% Trips with Recharge** |
|---|---|---|---|---|
| $\mathbf{k_1}$ | $\mathbf{k_2}$ | | | |
| 0.1 | 0.7 | 0.89 | 19.25 | 2.19 |
| 0.2 | 0.6 | 0.93 | 18.65 | 2.22 |
| 0.3 | 0.5 | 0.96 | 18.31 | 2.24 |

that increase battery consumption (and thus recharge times) and travel times. This small comparison suggests that our generated routes are basically the same as ABRP (ref. the very small distance differences) and the impact indicators we compute, expressed as relative increase/decrease of times, are overall coherent with ABRP (ref. the stable percentage difference in recharge and overall times).

### *D. Case studies*

In this section we closely examine the impact of EVs on four sample users, each under two scenarios: charge at home and work, and charge only at public stations. User A is characterized by a moderate number of recharges performed (12 in the worst case), while user B had a higher number (28 in the worst case). Figures 8 and 9 show the results respectively for user A and user B, adopting a double visual representation of the EV-based mobility for each scenario: the Individual Mobility Network (IMN) one (top) depicts user's locations as nodes and trips as edges, representing visit/trip frequency as thickness and recharges as redness; the temporal charge one (bottom) shows the charge in time, using red for recharges at stations and green for passive ones.

The IMN representation in Figure 8(top-left) shows that in the public-only scenario user A performed several recharges along different trips of their history (see the red edges), plus rather frequent passive recharges (i.e. while stopping at a trip destination) in two locations (see the small red nodes). The temporal charge plot on the bottom-left also confirms that recharges at stations (in red) are approx. uniformly distributed in time, while passive recharges (in green) are less frequent. The corresponding home + work scenario is shown on the right plots. As we can see, recharges are now much more concentrated on the home and work location, significantly reducing the recharges at stations (especially for trips starting/ending at home or at work) and also strongly reducing the other passive recharges. The temporal graph confirms this, and also shows that the battery level is generally kept much higher than in the previous scenario. For this user, the overhead in adopting an EV seems to be moderate, and reduced almost to zero when recharging at home and work is possible.

User B, shown in Figure 9, starts from a much more complex situation, as they require rather frequent recharges at public stations in the public-only scenario and do not benefit from passive recharges. Moving to the home and work scenario, recharges at home reduce significantly the usage of public stations, yet there is no dominant work place, and the overall result is that also in this scenario a significant number of stops at public stations is needed, especially in the central period of time. User B is not only energy-hungry, but their

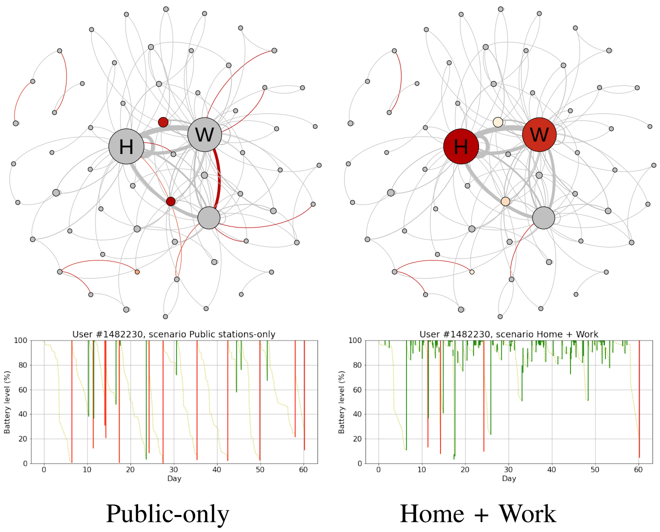


Fig. 8. ***Use case A**: IMNs (top) and temporal graph of charge (bottom). Left: Home + Work scenario; right: Public-only. Size and width in IMNs represent frequency of stop/trip, darkness of red represents frequency of recharge. In the temporal graph, passive charges are green, those at stations are red.*

mobility distribution also makes the effect of passive recharges less incisive. Overall, this appears to be a user that might require more effort in the transition to EVs.

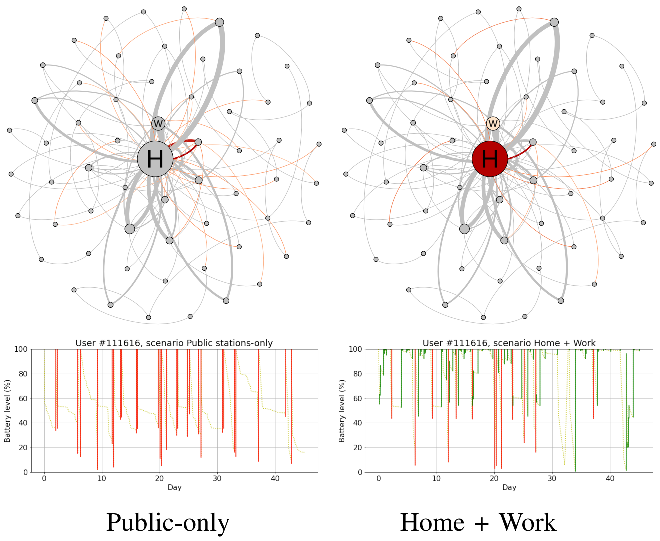


Fig. 9. ***Use case B**: same layout as Figure 8.*

Two more sample users are shown in Figures 10 and 11. User C (Figure 10), has a complex mobility that in the public-only scenario requires several recharges in several different stations, impacting many trips. Introducing Home and Work recharges virtually erases the need for public stations, just leaving a single recharge out.

User D (Figure 11), has an even denser IMN, with several charges that, in the public-only scenario, are very evenly spread across many stations. Also in this case, introducing Home and Work recharges strongly reduces the need of public stations, yet some trips are left out, especially in the second period of the simulation, mainly concentrated in a few routes, usually connecting locations without recharge options. We

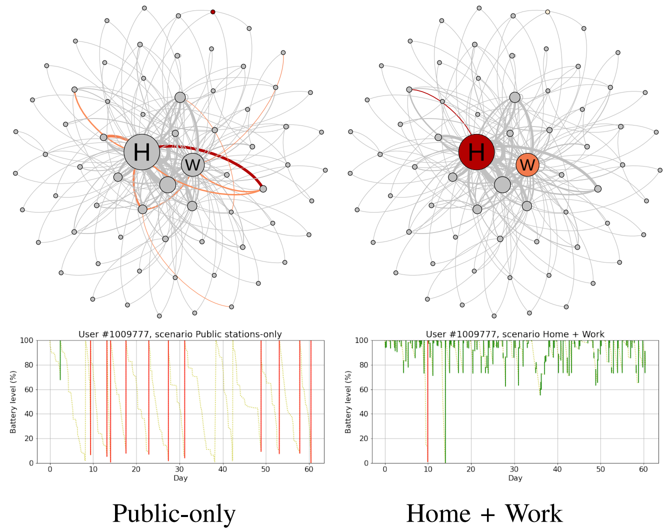


Fig. 10. ***Use case C**: same layout as Figure 8.*

also notice that a weak spot emerged in a third location (beside Home and Work), where *passive* charging at stations is performed while stopping in a nearby location.

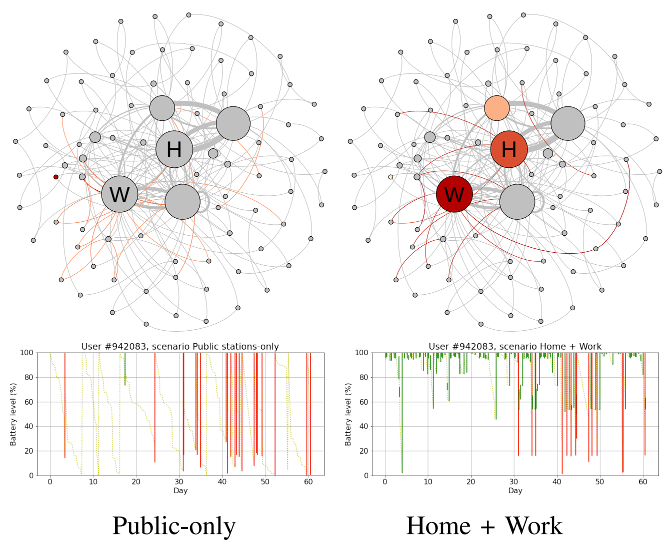


Fig. 11. ***Use case D**: same layout as Figure 8.*

## VI. Conclusions

In this work, we proposed a methodology based on mobility data analytics, ad-hoc trip planning and simulation, that provides detailed quantitative information about what the switch from ICEs to EVs can mean for single users and for the collectivity. The proposed approach is efficient – thus suitable for large-scale studies – and takes into consideration the main aspects involved in EV-based mobility: limited driving range, sparse recharge infrastructures, potentially long recharge times, the possibility of recharging at home/work, and so on.

**Use case results and application.** The results obtained over an Italian region show how the electrification process is expected to generate only moderate issues at the collective level (mainly, marginal increases in distance traveled and overall moderate time spent at recharge stations), and yet individual users can expect slightly different impacts in they travel & refuel habits. We envision that these results (and the tool in general) can help various actors of the mobility scene: decision-makers in better planning the charging infrastructures by simulating the impact of installing new stations or improving their speed; car makers to support the design of models that better fit users' needs; and the single users, that can better understand their personal fitness to EV under different conditions and car models (e.g. choosing their personal best trade-off between battery capacity and cost).

**Limitations and open problems.** Though a ready-to-use tool, the proposed approach is still amenable to improvements in several directions that we aim to explore: integrating/estimating waiting times at stations, as well as a more complete map of charge stations; considering the variability of power provided by chargers as effect of the time-variable energy grid load; studying the effect of different battery capacities; studying the impact of EVs on user costs and environmental factors; finally, devising processes and setting up experiments to achieve a stronger validation of results, and a better calibration of the tool.

## References


[1] A. Mahmoudzadeh Andwari, A. Pesiridis, S. Rajoo, R. Martinez-Botas, and V. Esfahanian, "A review of battery electric vehicle technology and readiness levels," *Renewable and Sustainable Energy Reviews*, vol. 78, pp. 414–430, 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1364032117306251

[2] S. Hosseinpour, H. Chen, and H. Tang, "Barriers to the wide adoption of electric vehicles: A literature review based discussion," in *2015 Portland International Conference on Management of Engineering and Technology (PICMET)*, 2015, pp. 2329–2336.

[3] T. Franke, N. Rauh, M. Günther, M. Trantow, and J. F. Krems, "Which factors can protect against range stress in everyday usage of battery electric vehicles? toward enhancing sustainability of electric mobility systems," *Human Factors*, vol. 58, no. 1, pp. 13–26, 2016, pMID: 26646301.

[4] C. Suarez and W. Martinez, "Fast and ultra-fast charging for battery electric vehicles – a review," in *2019 IEEE Energy Conversion Congress and Exposition (ECCE)*, 2019, pp. 569–575.

[5] M. A. Nicholas, G. Tal, and J. Woodjack, "California statewide charging assessment model for plug-in electric vehicles: Learning from statewide travel surveys," 2013.

[6] M. De Gennaro, E. Paffumi, G. Martini, and H. Scholz, "A pilot study to address the travel behaviour and the usability of electric vehicles in two italian provinces," *Case Studies on Transport Policy*, vol. 2, no. 3, pp. 116–141, 2014. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2213624X1400042X

[7] S. Rinzivillo, L. Gabrielli, M. Nanni, L. Pappalardo, D. Pedreschi, and F. Giannotti, "The purpose of motion: Learning activities from individual mobility networks," in *2014 International Conference on Data Science and Advanced Analytics (DSAA)*. IEEE, 2014, pp. 312–318.

[8] M. Nanni, O. Isfahani Alamdari, A. Bonavita, and P. Cintia. (2023, Mar.) From fossil fuel to electricity: source code, examples and auxiliary material. [Online]. Available: https://github.com/alamdari/EVSim

[9] S. Bigerna and S. Micheli, "Attitudes toward electric vehicles: The case of perugia using a fuzzy set analysis," *Sustainability*, vol. 10, p. 3999, 11 2018.

[10] S. Hardman, A. Jenn, G. Tal, J. Axsen, G. Beard, N. Daina, E. Figenbaum, N. Jakobsson, P. Jochem, N. Kinnear, P. Plötz, J. Pontes, N. Refa, F. Sprei, T. Turrentine, and B. Witkamp, "A review of consumer preferences of and interactions with electric vehicle charging infrastructure," *Transportation Research Part D: Transport and Environment*, vol. 62, pp. 508–523, 07 2018.

[11] A. Driscoll, S. Lyons, F. Mariuzzo, and R. S. Tol, "Simulating demand for electric vehicles using revealed preference data," *Energy Policy*, vol. 62, no. C, pp. 686–696, 2013. [Online]. Available: https://ideas.repec.org/a/eee/enepol/v62y2013icp686-696.html

[12] K. Coninx and T. Holvoet, "A microscopic traffic simulation platform for coordinated charging of electric vehicles," in *Advances in Practical Applications of Heterogeneous Multi-Agent Systems. The PAAMS Collection*, Y. Demazeau, F. Zambonelli, J. M. Corchado, and J. Bajo, Eds. Cham: Springer International Publishing, 2014, pp. 323–326.

[13] S. Bae and A. Kwasinski, "Spatial and temporal model of electric vehicle charging demand," *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 394–403, 2012.

[14] G. Handler and I. Zang, "A dual algorithm for the constrained shortest path problem," *Networks*, vol. 10, pp. 293 – 309, 10 2006.

[15] M. Baum, J. Dibbelt, A. Gemsa, D. Wagner, and T. Zündorf, "Shortest feasible paths with charging stops for battery electric vehicles," *Transportation Science*, vol. 53, 07 2019.

[16] A. Artmeier, J. Haselmayr, M. Leucker, and M. Sachenbacher, "The shortest path problem revisited: Optimal routing for electric vehicles," 09 2010, pp. 309–316.

[17] M. Baum, J. Dibbelt, T. Pajor, and D. Wagner, "Energy-optimal routes for electric vehicles," in *Proceedings of the 21st ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, ser. SIGSPATIAL'13. New York, NY, USA: Association for Computing Machinery, 2013, p. 54–63.

[18] M. Strehler, S. Merting, and C. Schwan, "Energy-efficient shortest routes for electric and hybrid vehicles," *Transportation Research Part B: Methodological*, vol. 103, pp. 111–135, 2017, Green Urban Transportation. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0191261516304404

[19] M. Baum, J. Dibbelt, L. Hübschle-Schneider, T. Pajor, and D. Wagner, "Speed-consumption tradeoff for electric vehicle route planning," in *ATMOS*, 2014.

[20] L. Perron and V. Furnon, "Or-tools," Google, 2022. [Online]. Available: https://developers.google.com/optimization/

[21] T. Sweda and D. Klabjan, "Finding minimum-cost paths for electric vehicles," 03 2012, pp. 1–4.

[22] T. Sweda, I. Dolinskaya, and D. Klabjan, "Adaptive routing and recharging policies for electric vehicles," *Transportation Science*, vol. 51, 03 2017.

[23] KIA Corporation. (2023) How to extend EV battery life? [Online]. Available: https://www.kia.com/dm/discover-kia/ask/how-to-extend-ev-battery-life.html

[24] R. Trasarti, F. Pinelli, M. Nanni, and F. Giannotti, "Mining mobility user profiles for car pooling," in *Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining*. ACM, 2011, pp. 1190–1198.

[25] R. Trasarti, R. Guidotti, A. Monreale, and F. Giannotti, "Myway: Location prediction via mobility profiling," *Information Systems*, vol. 64, pp. 350–367, 2017.

[26] R. Guidotti, R. Trasarti, M. Nanni, F. Giannotti, and D. Pedreschi, "There's a path for everyone: A data-driven personal model reproducing mobility agendas," in *2017 IEEE International Conference on Data Science and Advanced Analytics (DSAA)*. IEEE, 2017, pp. 303–312.

[27] Newmotion - Shell EV Charging Solutions UK Ltd. (2020) EV Driver Survey Report 2020. [Online]. Available: https://assets.ctfassets.net/ulfvrpf1itxm/1Qid6yJBwkLoAoTSgr9kYt/9c11d5bdc97b994d1e8772e929e46f57/0729NM04_EV_driver_survey_report_2020_EN_FINAL.pdf

[28] C. Canali. (2020) Auto elettrica, tutto quello che c'è da sapere sulla ricarica a casa. [Online]. Available: https://www.ilsole24ore.com/

[29] P. Probe. (2022) Assessment of the consumer electric vehicle charging experience in canada – final project report. [Online]. Available: https://www.pollutionprobe.org/wp-content/uploads/2022/06/Pollution-Probe-.Consumer-EV-charging-Experience.pdf

[30] J. Van Roy, N. Leemput, S. De Breucker, F. Geth, P. Tant, and J. Driesen, "An availability analysis and energy consumption model for a flemish fleet of electric vehicles," in *EEVC European Electric Vehicle Congress*, 2011. [Online]. Available: https://lirias.kuleuven.be/retrieve/162605

[31] G. Alvaro, Gonzalez and Fraile-Ardanuy, "Estimation of electric vehicles' consumption based on their mobility," Section 3.3.3. of Deliverable D6.1 of the DataSIM Project, 2013.

[32] E. W. Dijkstra, "A note on two problems in connexion with graphs:(numerische mathematik, 1 (1959), p 269-271)," 1959.

[33] A. Hagberg, P. Swart, and D. S Chult, "Exploring network structure, dynamics, and function using networkx," Los Alamos National Lab.(LANL), Los Alamos, NM (United States), Tech. Rep., 2008.

[34] M. Nanni, R. Guidotti, A. Bonavita, and O. Isfahani Alamdari, "City indicators for geographical transfer learning: an application to crash prediction," *Geoinformatica*, 2022.

[35] R. Guidotti and M. Nanni, "Crash prediction and risk assessment with individual mobility networks," in *2020 21st IEEE International Conference on Mobile Data Management (MDM)*, 2020, pp. 89–98.

[36] C. Lilly. (2022) Ev charging connector types. [Online]. Available: https://www.zap-map.com/charge-points/connectors-speeds/

[37] C. Tilk, A.-K. Rothenbächer, T. Gschwind, and S. Irnich, "Asymmetry matters: Dynamic half-way points in bidirectional labeling for solving shortest path problems with resource constraints faster," *European Journal of Operational Research*, vol. 261, no. 2, pp. 530–539, 2017.


**Mirco Nanni** holds a degree and a PhD in Computer Science (University of Pisa, in 1997 and 2002). He is currently a senior researcher at ISTI - CNR in Pisa, head of the KDD Laboratory. His research interests cover several aspects of human mobility, such as data mining on spatio-temporal data, applications on transportation and smart cities, mobile phone data analysis and Big Data for Official Statistics.

**Omid Isfahani Alamdari** received a B.Sc. and M.Sc. in computer engineering from Urmia University (2013) and Iran University of Science and Technology (2016), and a Ph.D. in Computer Science at the University of Pisa (2020). Worked for two years as post-doc at University of Pisa, and since 2022 is Lead Data Scientist at TELUS (Canada). His research interests include mobility big data, distributed systems, database systems and location-based services.

**Agnese Bonavita** has a BS degree in Physics (University of Genoa) and a M.S. in High Energy Physics (Pisa University). She is currently a Ph.D. student in Data Science at Scuola Normale Superiore (joint programme with Scuola Superiore Sant'Anna, University of Pisa, IMT Lucca and CNR - National Research Council), and her research focuses on human mobility models and prediction, in particular electric vehicles simulations and car accidents forecasting and risk assessment.

**Paolo Cintia** received the B.S. and M.S. degree from the Department of Computer Science, University of Pisa, and a Phd in Computer Science in 2015. His research activity is focused on Sports Data Science and Mobility Data Mining. He is co-founder of Playerank srl, a spin-off company of the University of Pisa keen on developing AI tools for Sports Analytics.

## Appendix

### A. Vehicle parameters

By default a medium class car model is considered in our simulations. The vehicle parameters are the following:

- Cross section area 2.27 $m^2$
- Machine weight 1521 kg
- Driver weight 90 kg
- Aerodynamic drag coefficient 0.29
- Rolling resistance coefficient 0.012
- Regeneration ratio 0.25 default / 0.35 in eco mode
- Battery capacity 40kW
- Low battery limit 8-10%
- Transmission efficiency 0.95
- Machine and electric motor efficiency 0.98
- Battery charging efficiency 0.95
- Battery discharge efficiency 0.98

These settings can be easily changed by modifying a configuration file, where all parameters are listed.

### B. Detailed battery consumption model

Our estimation of battery consumption for each trip of the user is based on a instantaneous consumption model introduced in [30] and recommended in [31] as a good trade-off between realistic simulation and efficient computability. The model considers all the physical forces to which the vehicle is constantly exposed in order to estimate the amount of electric power needed to reach a certain speed, which are illustrated in figure 12.

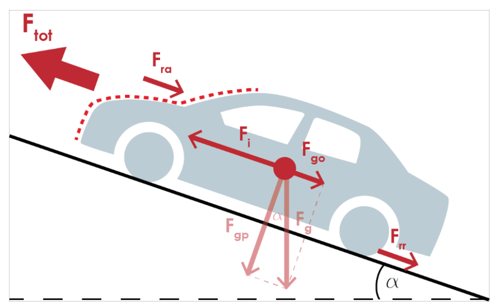


Fig. 12. The physical forces to which a vehicle is exposed during the movement

The model is general and can be adapted to each type of vehicle changing specific parameters. In details it considers:

- Rolling resistance: $F_{rr} = R(M_{car} + M_d)gcos\alpha$. Where $R()$ Is the rolling resistance coefficient of the tire, $M_{car}$[kg] is the mass of the vehicle, $M_d$[kg] is the mass of the driver, $g$= 9.81 [m / s2] is the acceleration of gravity and $/alpha$ [rad] is the angle of the surface on which the machine is located with respect to the horizontal plane.
- Aerodynamic resistance: $F_a = \frac{1}{2}AC_d\rho v^2$. Where $A[m^2]$ is the area of the front surface of the vehicle, $C_d$ is the aerodynamic drag coefficient, $\rho$= 1.2041 [kg / $m^3$] is the density of the air at 20°C and $v$[m/s] is the vehicle speed.
- Horizontal component of gravity: $F_{hc} = (M_{car} + M_d)gsin\alpha$

- Inertia: $F_{la} = 1.05(M_{car} + M_d)a$. Where $a$[m/$s^2$] is the acceleration of the vehicle.

Hence, the total pulling force can be expressed as $F_{tot} = F_{rr}+F_a+F_{hc}+F_{la}$. Mechanical traction power is the product of the traction force and the average vehicle speed. It depends on the engine power and transmission efficiency and is: $P_{tot} = F_{tot}v$. This power is transferred to the wheels, and assuming an efficiency of the gears, the resulting power is:

$$P_{engineOut} = \frac{P_tot}{\eta_{gear}}$$

The efficiency of the engine is then considered and the power that enters is:

$$P_{engineIn} = \frac{P_{engineOut}}{\eta_{engine}}$$

The auxiliary power $P_{aux}$, which represents the power necessary for lights, air conditioning, radio, and other electrical appliances in the vehicle is considered as: $P_{consMov} = P_{engineIn} + P_{aux}$.

During breaking, cars must remove its kinetic energy converting it into heat. Electric Vehicles have regenerative breaking that can recover a fraction $R_{genRatio}$ of such energy to recharge the battery. In this case the mechanical power is negative, $P_{te}$¡0, and this variable will be weighted by the regeneration factor and flow back from the wheels to the motor (working in generation mode) and to the battery: $P_{teReg} = R_{genRatio}P_{te}$.

The next step is taking into account the transmission efficiency. The power going out from this block to the electric machine-power electronics block is given by: $P_{regEngineOut} = \eta_{gear}P_{teReg}$. The power going out from the electric machine-power electronics block to the battery is given by $P_{regEngineIn} = \eta_{engine}P_{regEngineOut}$, and the final amount of energy is thus: $P_{finalBattery} = P_{consMov} + PregEngineIn$.

The resulting model for charging and discharging [30] of the battery must consider the energy transmission efficiency coefficients: $\eta_{charge}$ and $\eta_{discharge}$, thus the two operations produce energy as:

$$E_{bat} = \frac{P_{finalBattery}.\Delta t}{\eta_{discharge}}$$

$$E_{bat} = \eta_{charge}P_{finalBattery}.\Delta t$$

Therefore the variation in capacity will be:

$$\Delta Soc = \frac{E_{bat}}{E_{bat}^{CAP}}$$

where $E_{bat}^{CAP}$ is the maximum capacity of the battery. Considering the variation as function of the time $t$ the following model is obtained:

$$SoC[t] = SoC[t-1] - \Delta Soc - \delta_{self_disch}$$

where $\delta_{self_disch}$ is the self-discharge losses.