Load curve impact of large electric vehicles fleet in the Paris Ile-de-France region

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Introduction

Several countries promote Pure and Plug-in-Hybrid electric vehicles because they can provide an appropriate technological answer to the EU's energy and environmental goals. However, quantifying their benefit is complex since electromobility poses specific challenges in terms of timescale, sector coordination and infrastructure. The overall objective of the EV-STEP project was to quantify some of the technical and economic conditions of the development of electrified mobility in Europe by 2030 and beyond. In complement to the EU-scale evaluation based on the TIMES pan-EU and IMACLIM-P models, additional case studies were defined in the EV-STEP project's methodology to investigate dedicated local issues with a higher level of technical detail. The EV-CAP model developed within EV-STEP is described in the first part, while the second part reports insights on the potential load curve impact drawn from a local case study of the Paris Ile de France region.

EV-CAP consists of various modules linked together. Downstream from the electromobility system, the challenge is to make electric vehicles correspond with society-driven mobility needs supplied by personal cars (e.g. the pattern of individual trips required during a set of typical days by each electric vehicle in a fleet). Upstream, the distribution system imposes availability constraints on the power demand (physical context) and electricity price signals (economic context). The interaction of these two systems is then materialized by an infrastructure of battery chargers characterized by different authorized current levels. This includes the possibility of discharging vehicle batteries into the grid. EV-CAP combines statistical analyses with an MIP optimization step. The statistical information comes from the 2008 French national transport survey. The optimizer extends previous work done within the Infini Drive project.
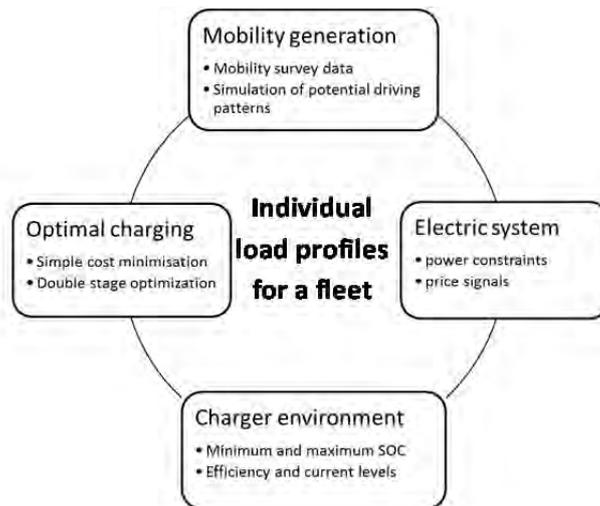
Figure 0-1. EV-CAP's module interaction

The model was conceived as a flexible platform for testing various assessment conditions of the electric vehicle fleet charging problem. The specification of a case study consists in selecting parameter values (mobility, charging or cost-signal related inputs) for each dimension. For the EV-STEP project, 63 cases were designed in order to understand the induced change in the power demand curve for a representative working day, with a 15mn time step, and according to varying simulation conditions: charging intensity, charging behavior, price signal, vehicle-to-grid, and type of electric vehicle. The statistical mobility demand module generated 1500 trips for 500 individual cars on a typical working day.

Examples of characteristic load curves for electric vehicles can be found in the literature. For instance, [1][2] reports three benchmark load curves proposed by the French transmission system operator RTE to evaluate the impact of EV charging. In [3] the JRC proposes an analysis of possible load curve impact for several EU countries. Both state that the impact could be significant if unmanaged and point out the lack of studies. The advances proposed here include: price signal effects, the behavior prior, charging level and vehicle-to-grid capability. The second part proposes an analysis of the Ile-de-France region. We explore the alternative computed EV load curve and then discuss its potential impact on the current IDF load curve.

Part 1) Description of EV-CAP methodology for electric vehicle fleets

1.1 Mobility generation module

The purpose of the mobility generation is to define a set of trips to be satisfied based on statistical information extracted from mobility surveys. For the Paris Ile de France case study, the EGT ("Enquête Globale Transport") 2010 [4] [5] [6] and the ENTD 2008 national [7] [8] transport survey are two examples of surveys with individual trip data. Due to easier access to raw data and our focus on mobility supplied by personal vehicles, we used the ENTD survey. This choice also allows similar treatment of other urban environments in France. Note that comprehensive mobility surveys are currently carried out and published every 7 to 10 years. The advantage of using a synthetic generator (instead of taking trips directly from the survey) is the ability to generate new patterns by selectively changing the value of the descriptors in alternative scenarios. It also enables us to freely specify the number of vehicles in each case study.

The generator constructs yields synthetic trips that generally follow the controlled statistical data extracted. The aggregated metropolitan area is disaggregated into smaller zones exhibiting original patterns. Three zones are identified: Paris, the "Petite Couronne" which is the city's inner ring (PC), and the "Grande Couronne", which is the outer ring (GC). The overall process of statistical information extraction from the national mobility survey is shown in Figure 1-1. The mobility survey is used to characterize two dimensions: mobility pattern and vehicle parking location. The mobility module only deals with the mobility pattern analysis. Its main descriptors within EV-CAP are discussed below. Parking habits are dealt with in the post treatment (section5) for an initial geographical distribution.

```
┌─────────────────────┐                          ┌─────────────────────┐
│      Raw file       │                          │  Raw local trips file │
│      Q_ménage       │                          │      K_deploc       │
│  From MDDE website  │                          │  From MDDE website  │
└─────────────────────┘                          └─────────────────────┘
```
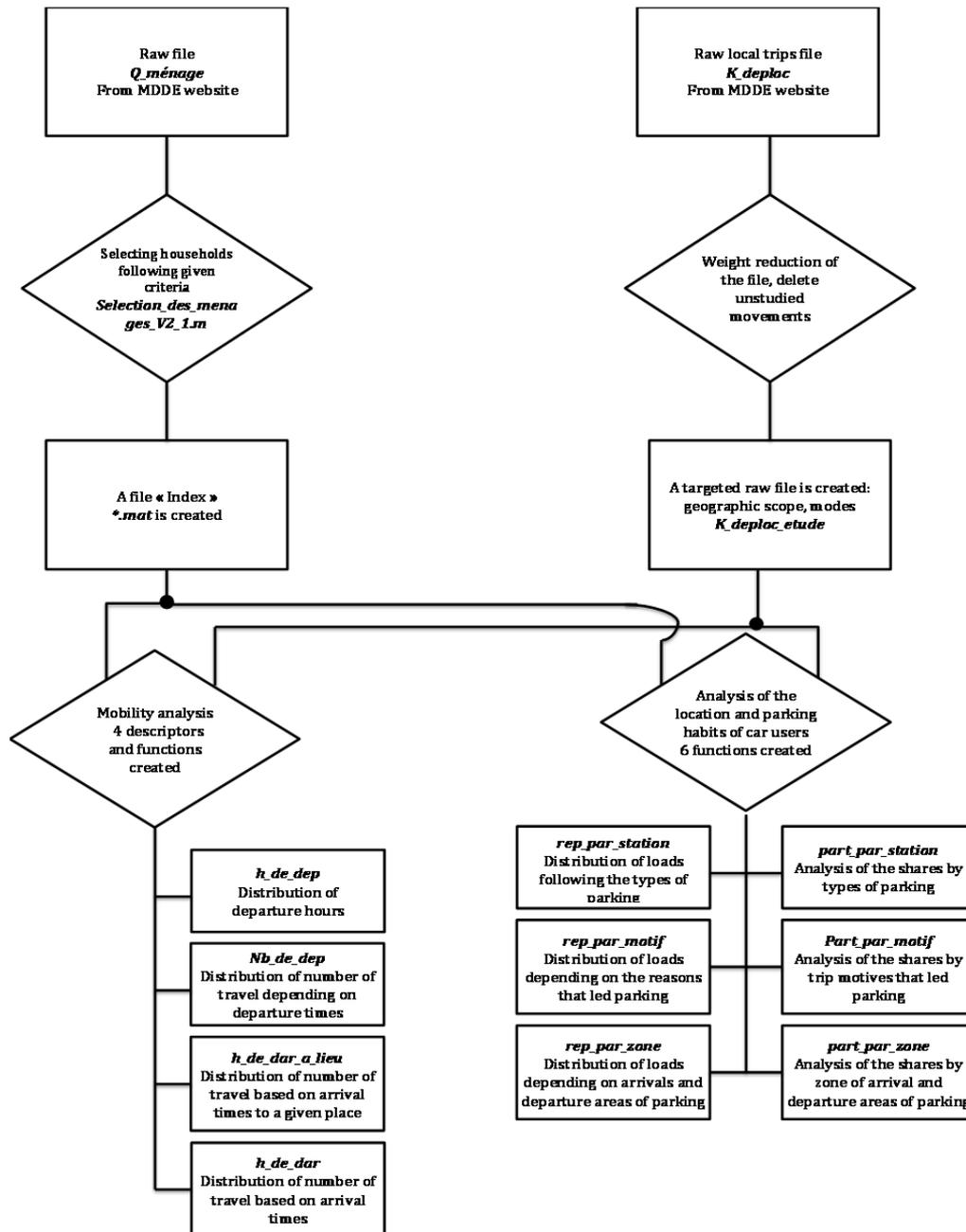
Figure 1-1: Functional description of the statistical mobility analysis

1.1.1 Number of trips per day

The number of trips per car user per day is extracted for each zone of interest. For the Paris IDF area as a whole, the average trip demand is 3.31 trips per day. However, directly using this value would be misleading as the average deviation for all recorded trips is 1.85. The discrete distribution of number of trips is the preferred descriptor (Figure 1-2). It shows that making 3 trips per day is clearly not the most common behavior in the Paris IDF area as a whole and that more than 30% of car users still make 4 trips or more. The same type of distribution is retrieved for each sub-region to capture the differences in discrete (and integer) trip demand.
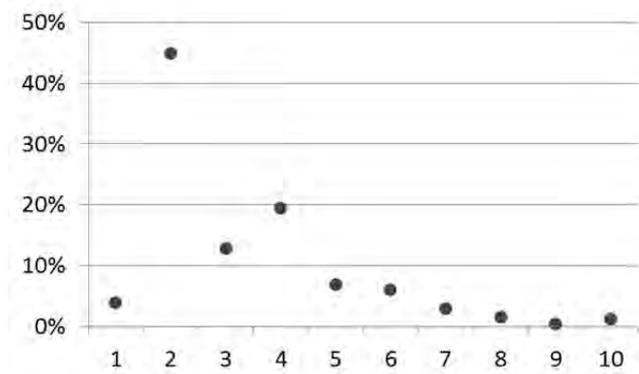
Figure 1-2. Illustration of a discrete distribution of number of trips for the Paris Ile de France area

1.1.2 Trip duration

The trip duration per day is also analyzed as it not only reflects driving habits but shows, from an electric vehicle point of view, the amount of time during which no charging is feasible. As for the number of trips per day, the distribution is used as a descriptor for each zone. The average duration is 72mn for the IDF region (with 94 mn for Paris) but 20% of users spend more than 2 hours per day driving in total. Figure 1-3 illustrates the difference in car trip duration for the area as a whole and for the three representative zones.
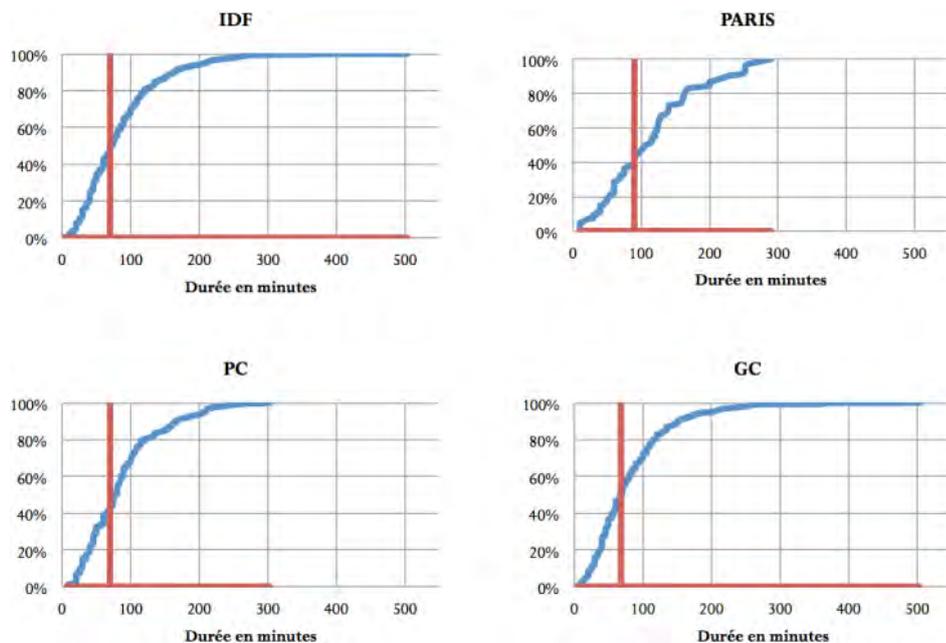
Figure 1-3. Distribution of daily car trip duration in mn for the Paris Ile de France area

1.1.3 Departure times

The goal here is to coherently represent the scheduling of daytime car trips. This is important in the interaction between mobility patterns and electric networks as it gives the feasible time space for charging and discharging events. The characteristic distribution of departure times for a typical weekday is extracted from the mobility survey for each departure zone. It exhibits 2 more or less pronounced peaks around 8 AM and 6 PM; it also shows intermediate peaks in car trip demand of variable size.
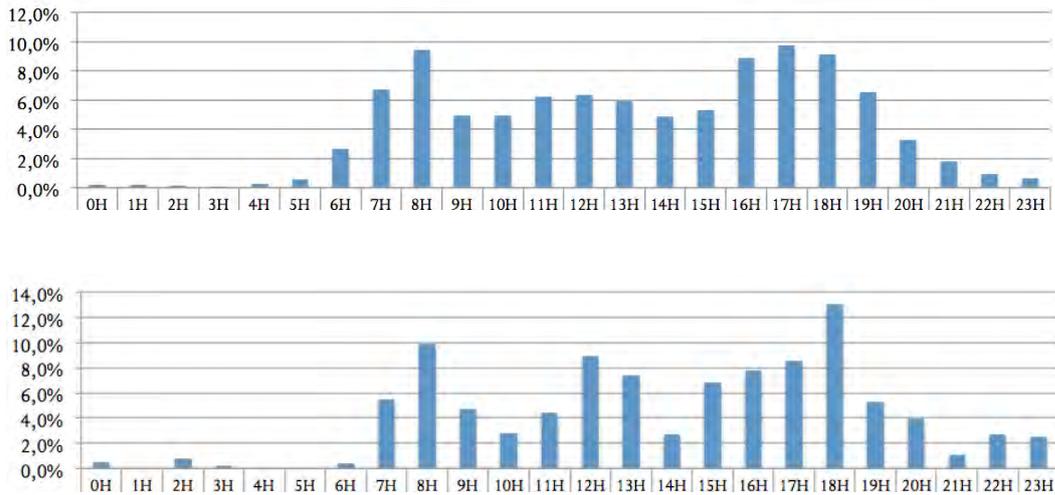
Figure 1-4. Departure time distribution for the Ile de France area as a whole (top) and Paris (bottom)

To consistently associate numbers of trips with departure times, the departure profiles are further refined by their dependency on the trip number (for the 1st, 2nd, and following trips of the day).
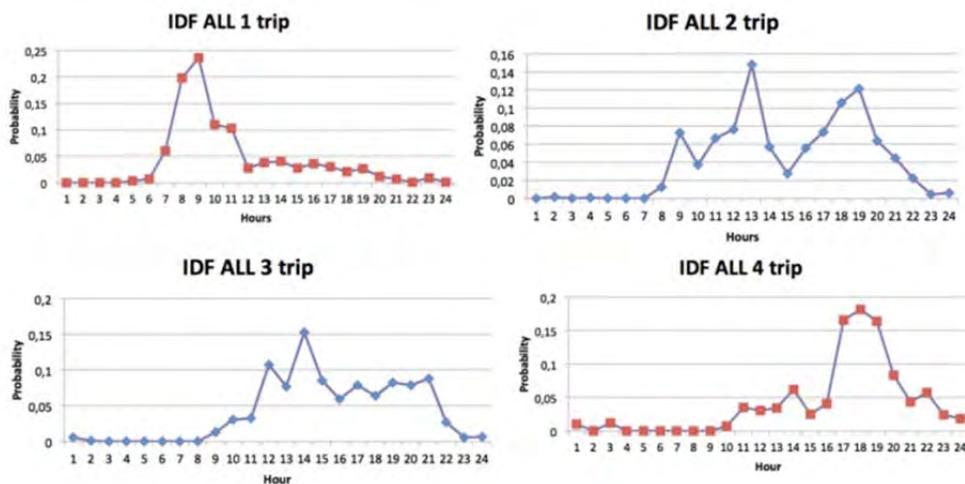
Figure 1-5. Illustration of departure time distribution for the Ile de France by trip number

1.1.4 Extending the mobility analysis to specific segments or niche markets

A common underlying assumption when assessing the future driving patterns of electric vehicles is that they should be compatible with average conventional car usage. Yet electric vehicles are currently developed via policy incentives in specific captive markets and could in the future be concentrated in atypical markets. Framing the statistical behavior of such potential markets is thus important. The methodology developed here handles this issue by restricting the statistical analysis of mobility characteristics to "niche markets", i.e. the 20%[1] most mobile users and the 20% least mobile users. The rationale is that the most mobile drivers could theoretically have more incentive to use an electric car as the battery cost can be amortized by more trips. Inversely, assuming a high range anxiety, the incentive could be higher for drivers making fewer trips. As illustrated in Figure 1-6, the mobility profile of these drivers differs significantly from the average in terms of the distribution of number of trips per day.

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1 The range of 20% considered is our choice within Ev-step and can of course be adjusted
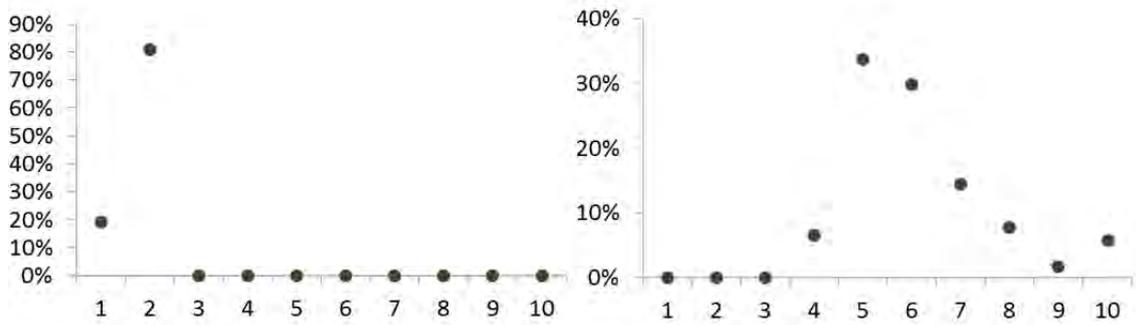
Figure 1-6. Illustration of number of car trips per day for two extreme niche markets: low (left) and high (right) mobility

1.2 Electric system and charging environment

The electric system and charging environment modules then model the integration of electric cars into the electric network as a new source of power withdrawal, and eventually supply, in a vehicle-to-grid mode. The physical limitation and costs of power and the management of battery energy demand in the electric car are the two main sides of this interaction considered in EV-CAP.

1.2.1 Available capacity

What is the cumulated load curve effect of a massive development of electric vehicles? Will the additional power demand bring the system too close to or take it beyond acceptable operational boundaries during one day? If so, at what time of the day does it occur? This is modeled in EV-CAP with the notion of available power. It can vary with time during the day and is introduced as a constraint to the charging problem.
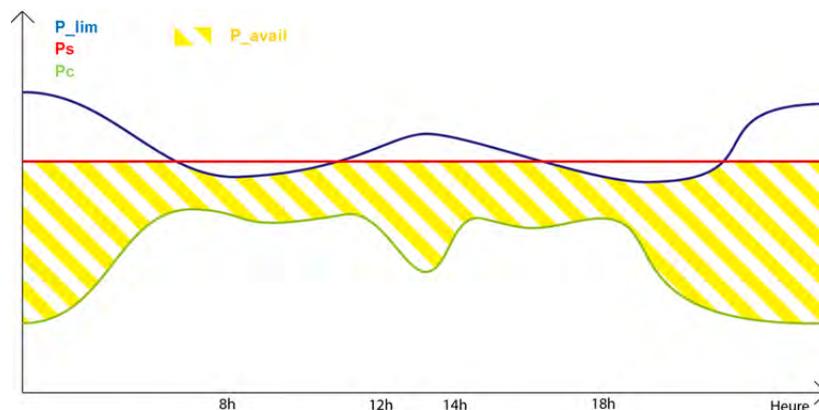
Figure 1-7. Power concepts introduced into EV-CAP

Figure 1-7 summarizes the interplay between the different concepts and mechanisms considered. For a given region of interest, Ps is the subscribed power and represents the maximum power specified in the supply contract. Pc is the power that is already used for all the other electric usages included in the same contract. Pc is usually lower than Ps in real life, as dissuasive penalties are charged each time a consumer exceeds the Ps. From an electric vehicle fleet perspective this represents the existing consumption of all other electric devices. In fact, if all consumers were to simultaneously withdraw the maximum Ps power allowed by their contract, the voltage on given network branches could vary significantly. P_lim is the physical power limit on the network. In real systems, this is a time-dependent constraint and could, during peak periods, be below the total contractual power. In our vehicle recharge problem, all of these time-dependent power concepts converge in an available power constraint, which is the difference between Pc and the minimum between {Plim,Ps}.

Practically, in EV-CAP, Pc(t) and min(Plim,Ps)(t) two series can be exogenously specified for the charging problem. Note that in vehicle-to-grid (V2G) mode, each battery discharge event towards the grid is equivalent to negative consumption and thus relaxes the power availability constraint.

1.2.2 Battery and charger environment

The battery and charger environment module describes the technical specifications and operation preferences applicable to the charging infrastructure and battery usage. It is modeled via the following descriptors.

1.2.2.1 Energy consumption per km

From an electric drive train perspective, energy consumption per km is described according to [3] as a quadratic function of the speed where A, B, C are calibrated constants:

$$\text{Energy consumption} = A * \text{Speed}^2 + B * \text{Speed} + C$$

The relationship obtained is used in EV-CAP for the energy demand of pure electric vehicles. For plug-in hybrid vehicles, the results of the G4V project are used [9]. Two types of PHEV are described: a PHEV90 and a PHEV30 with respectively 2/3 and 1/3 of their energy needs supplied by the battery. In the current version of EV-CAP methodology, PHEVs are hence modeled as equivalent to a pure electric vehicle with a reduction factor (1/3 and 2/3) of electricity demand for each km and an adjusted total battery capacity. The allocation between electric and conventional fuel is hence maintained constant for each trip.

	Elec (kWh/km)	Convent (l/100km)	Capacity (kWh)	Share elec
PHEV90	0.15-0.25	7.5	12-18	2/3
PHEV30	0.15-0.25	7.5	6-12	1/3

Table 1-1. Selected characteristics of energy consumption in PHEV mode

1.2.2.2 Range anxiety

The battery capacity limitations effectively perceived by drivers are not just purely technical. For a given battery capacity specified by a manufacturer, the observed behavioral effect of electric car drivers illustrated in [10] is known as range anxiety, which refers to the driver's fear of being stranded on the road. Electric vehicle owners may thus concretely restrain their usage range below what is technically possible in terms of battery capacity. In TECO's experiment, vehicle users returned their electric vehicles with over 50% state of charge in the absence of the psychological security of a fast charging possibility. On cars equipped with a fast charger, the charger was only occasionally used but the service area was widely covered.
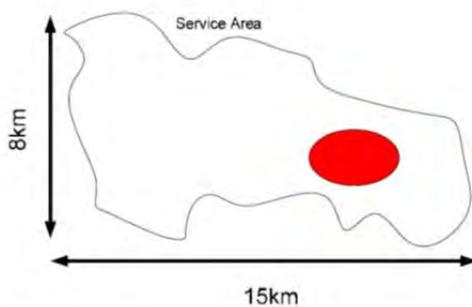
Figure 7: Service Area accessed by EV w/Slow Charger   Figure 8: Service Area accessed after Fast Charger added
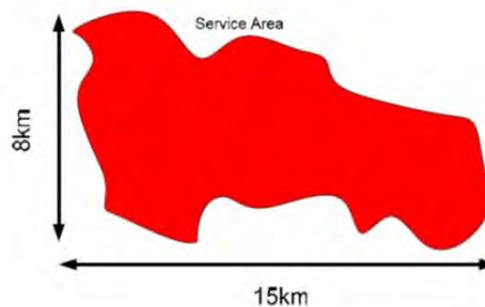
Figure 1-8. Illustration of range anxiety effect [10]

This barrier to EV usage is considered in EV-CAP by specifying the state of charge boundary conditions: SOC min and SOC max. They are expressed as a percentage of the total capacity.

1.2.2.3 Charger description

The charging infrastructure recharges the battery to? a given efficiency and within specified current charging boundaries. Slow charging from a regular electric socket involves current levels of typically 8-16A, while fast-charging solutions can support currents from 63A to 120A (direct or three-phase). The authorized current levels for a given simulation in EV-CAP are modeled as a list

of discrete steps between a maximum and a minimum. This allows the description of mode 2 to mode 4 chargers. The charging infrastructure can also be customized to allow a vehicle-to-grid (V2G) operation mode with discrete discharge levels and discharge intensity. Finally, charging efficiency can be modeled as dependent on charging intensity. The default charging efficiency is 0.81, which results from an efficiency of 0.9 for both the cell and the battery management system.

1.2.2.4 Price signal responsiveness
We also consider responsiveness to the electricity purchase price signal. One important advantage of electric vehicles frequently put forward is the significant reduction in fuel costs for the owner. On the downside, marginal gains can be low and drivers are receptive to average price rather than the "form" of a time-of-use price or a dynamic price scheme. Hence charging times become indifferent to the price at each time step. The relevant price signal can be freely adjusted to reflect a time-of-day pricing type, a simple average price signal, or to have more complex shapes. The price signal can also simulate a time-dependent premium payment for electricity supply to the grid in V2G mode.

In EV-CAP, the electricity price signal is specified as a function of time and can be differentiated for supply to the grid or withdrawal from the grid.

1.2.2.5 Other descriptors of the charging environment
An additional parameter of the battery/charger environment that is controlled in EV-CAP is the maximum number of charging events during day. Here the optimistic case would be an unbounded situation where all electric car users are reactive and willing and able to charge their vehicle as many times as needed. Less optimistic conditions could impose a constraint on the number of charging events with the extreme case of authorizing only 1or 2 charging events. These case-specific conditions are modeled in EV-CAP as a limit to the number of discontinuities in the reload profile over time, which directly reflects changes in charging decisions.

Additionally, in a full smart grid vision cost and total power can be collectively optimized. This additional control of cumulative electric load is possible in EV-CAP as a secondary objective and is introduced in the next section.

1.3 Vehicle charging/discharging module

We now describe the basic principles of the load profile computation step. What is the optimal charging schedule for each vehicle in a given electric vehicle fleet? And what is the aggregated load impact? This is assumed here to be the solution of an integer optimization problem that searches optimal and discrete charging events with a 15-mn time resolution. The optimization code development benefited from initial work carried out on the French Infinidrive project for a captive fleet of a few vehicles. The planning of charging or discharging events is determined for a cost function associated with electricity consumption that can in the absolute be the energy or carbon "cost" per kWh. Two additional objective functions were considered for a control of maximum load and in the shape of this load.

1.3.1 Overview of objective function formulations

1.3.1.1 Formulation1
The main objective in the first formulation is to minimize the charging cost, which is concisely written as follows:

$$minimize\left(\sum_{v \in VE} \sum_{t \in Time} \sum_{n \in Lev} b_{v,t,n} * Pc_k * Celec_t \right)$$

Where
- $v \in VE$ is the index of vehicles in the total fleet VE

- time $t \in Time$

- Charge levels : $n \in Lev$

- Pc_k the authorized charge levels

- The electricity associated cost at time t : $Celec_t$

- $b_{v,t,n}$: boolean decision variable

Subject to

- Mobility schedule constraints for each vehicle and each time slice: function of trip start Tdv,i and trip end Tfv,i times. Exclusion period for charging events.
- Energy needs: $E_{v,i}$ needed for each vehicle v and each trip i.
- Electricity environment and charger constraints: available power, discrete charging levels, battery capacity
- End-of-day continuity: for each vehicle the state of charge at the beginning and end of the horizon are the same
- Limits on maximum and minimum state of charge: Socmin, Socmax
- Additional option to constrain the number of charging events for each vehicle

The goal is then to minimize a charging cost with constraints that only apply to satisfying the demand for individual trips and the specifications of the electric system and charger environment.

1.3.1.2 Formulation 2

Formulation 1 freely minimizes the cost of charging. To model a full load control situation where the decision can be piloted to minimize the maximum load requires another formulation of the objective function: this is modeled in EV-CAP as a two-step optimization process where the maximum power demand is minimized as a secondary objective while taking the cost computed by the first objective function as a constraint. A tolerance factor expressed in percent specifies the cost relaxation allowed.

$$minimize \left(max_{on\ t} \left[\sum_{n,v\ \in Niv,VE} b_{v,t,n} * Pc_k \right] \right)$$

Subjtect to

$$\left(\sum_{v \in VE} \sum_{t \in Temps} \sum_{n \in Niv} b_{v,t,n} * Pc_k * Celec_t \right) \leq Sol_{ref} * (1 + Tol)$$

Where

- The solution of the primary cost minimization objective: Sol_{ref}
- The tolerance on the cost function for the secondary objective function: Tol

1.3.1.3 Formulation 3

Formulation 3 is then an extension of formulation2. Here additional conditional rules are added to constrain the problem to impose an a priori shape to the charging problem. This shape reflects additional behavioral knowledge such as: preferred time of charging distributed as time of return home. As illustrated in Figure 1-9, the additional knowledge is extracted from the statistical analysis of mobility surveys.
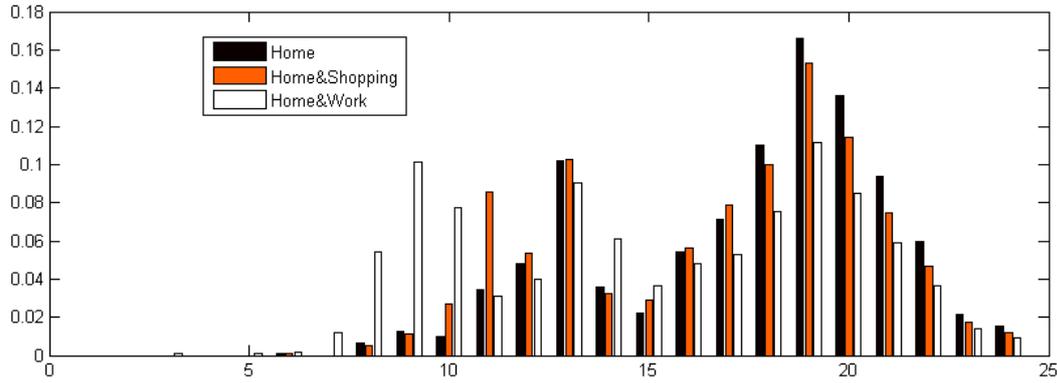
Figure 1-9. Distributions of arrival times: IDF all zones from 2008 national transport survey

This objective function is similar for "formulation 2" with a time-dependent envelope multiplier. At the minimum the power profile will then tend to follow the envelope while keeping the total charging cost within a tolerance window.

$$minimize\left(max_{on\ t}\left[\sum_{n,v\ \in Niv,VE} b_{v,t,n} * Pc_k * envel(t)\right]\right)$$

Subject to

$$\left(\sum_{v\in VE}\sum_{t\in Temps}\sum_{n\in Niv} b_{v,t,n} * Pc_k * Celec_t\right) \le Sol_{ref} * (1 + Tol)$$

Where

- The solution of the primary cost minimization objective: *Sol_{ref}*
- The tolerance on the cost function for the secondary objective function: *Tol*
- *envel(t)* is the vector of exogenous shape coefficients for each time step

1.3.1.4 Arguments

Table 1-2 sums up the problem parameterization options that are available to customize the electric vehicle optimization problem within EV-CAP. In practice they are specified as *.ini files that fully characterize the set of battery and charger environment conditions that define a given scenario case.

Arguments	Comment
-h, --help	show this help message and exit
--hour HH:MM	planning start time, default = 04:00
--days n	planning length in days, default = 1
--dt n	time step in minutes, default = 15
--socini	percent SOC(t0) initial value, default = 50.0
--socmin	percent SOC(t) t0<t<tf minimal constraint , default = 20.0

--socmax	percent SOC(t) t0<t<tf maximal constraint , default = 100.0
--socend	percent SOC(tf) minimal end constraint , default = 50.0
--reloads n	maximal number of reloads per vehicle, default = 3
--rlevels list	list of intensity reload levels, default 8,12,16
--dlevels list	list of intensity discharge levels, default = None
--capacity float	vehicle capacity (kWh), default = 22.0
--gap percent r	relative precision on first objective % , default = 2.0
--addgap percent	relative precision on second objective %, default = 2.0
--addtol percent	first cost increment for second objective %, default = 2.0
--limit n	limit time in seconds, default = 600
--ite n	max iterations, default = 1000
--silent	no message, default = False
--graphics	graphic mode, default = False

Table 1-2. Optimization parameters

1.3.2 Trip generator and sample size effects

Based on statistical descriptors extracted from the survey, the trip generation module computes the individual driving patterns of all cars in a fleet. Hence for every 15mn of a representative day, it produces a synthetic set of trips for n electric vehicles where the size is exogenously specified for a given study. Figure 1-10 to Figure 1-12 depict the outcome of the generation process when the number of vehicles changes. They represent the cumulated number of vehicles that are driving for each time period. Some basic observations can be made:

- For small fleets, the simultaneity, which is the percentage of vehicles driving at a given time, seems to reach higher values. The behavior does not necessarily follow a clear pattern;
- The higher the number of vehicles, the closer the distribution of a random selection to the original statistical characterization;
- Since most car trips last less than one hour, a sub-hourly resolution is preferable because it gives a more representative vision of the simultaneity than one-hour aggregated shares
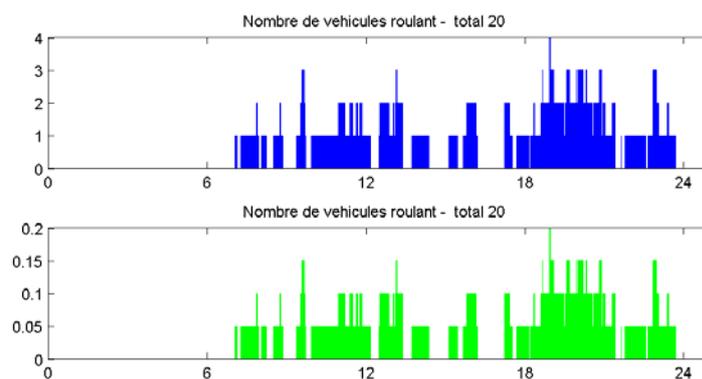
Figure 1-10. Trip generation20 vehicles
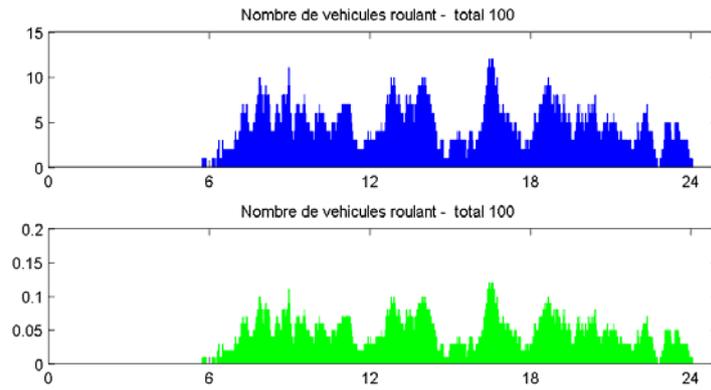
Figure 1-11. Trip generation 100 vehicles
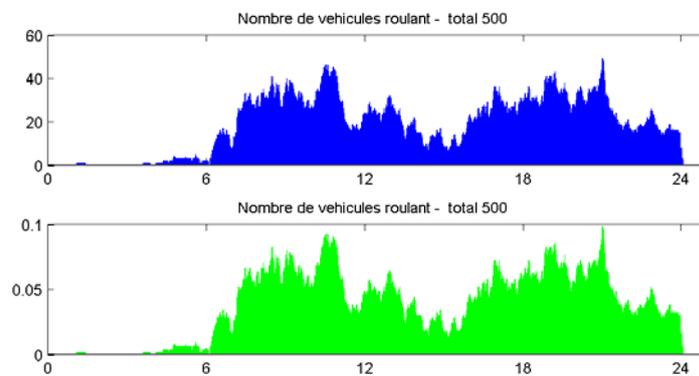
Figure 1-12. Trip generation 500 vehicles

1.3.3 Aggregated power demand indicators

After optimization corresponding to the appropriate problem formulation, the scheduling of the charging of each vehicle also yields an aggregated load in kW for each time step. This profile reflects the overall cost minimization strategy given the driving conditions, the electric system environment, and the specified battery-charging environment.

From this disaggregated basis, a kW/vehicle ratio can then be calculated as an indicator of the average load impact of one electric vehicle. It gives the time-dependent characteristic load per vehicle.

The state of charge is expressed as a percentage of total battery capacity. Two state-of-charge indicators are also computed:

- SOC_Raw: this indicator provides the state of charge at each time step and for the whole fleet based on the data of each individual vehicle.
- SOC_Net: this second indicator provides the state of charge at each time t excluding vehicles that are circulating or charging. It is the net additional capacity that could theoretically be available for discharge in V2G mode.
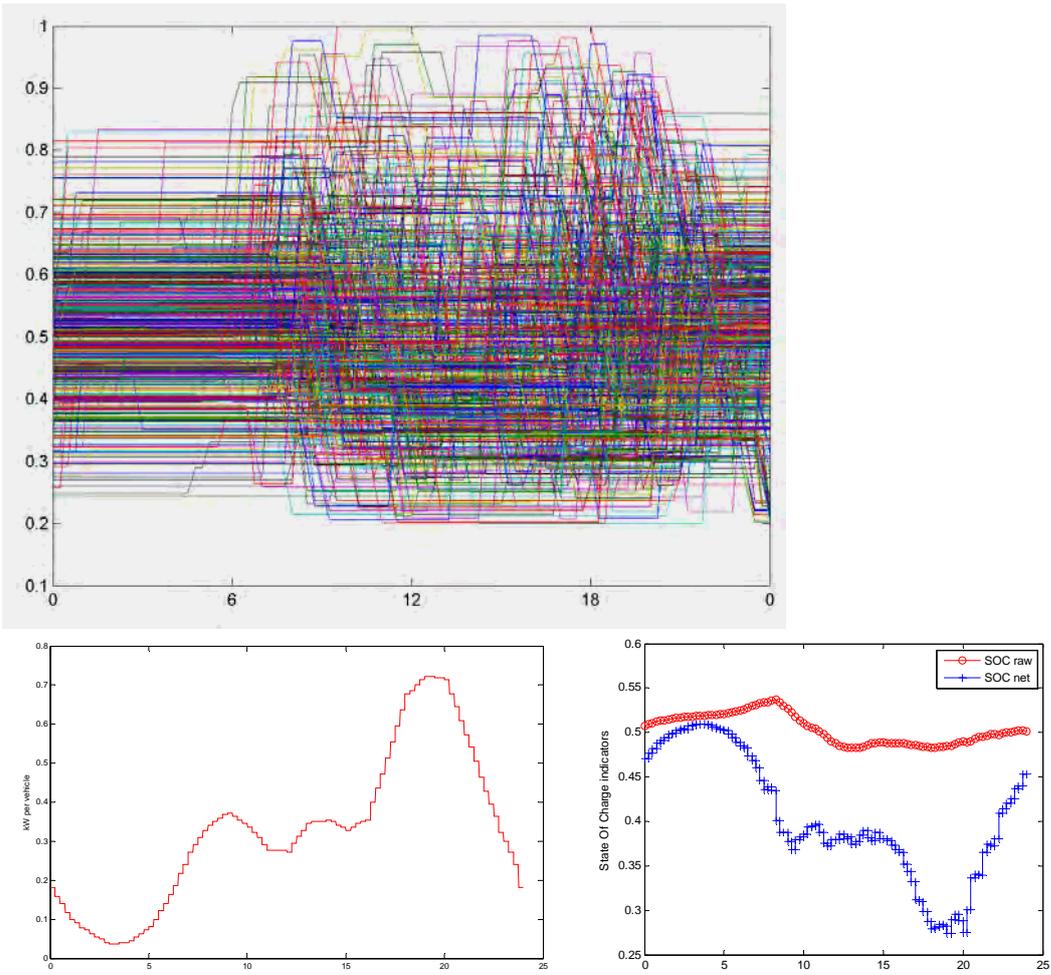
Figure 1-13. Illustration of the power demand indicators in kW for one vehicle. a) individual state of charge, b) overall load impact indicator per vehicle, c) state-of-charge indicators

Part 2) Analysis of the Paris Ile de France area using EV-CAP methodology

2.1 Characteristic EV load curves

Alternative EV charging load curves were computed for various charging contexts. The scenario tree in Figure 2-1 outlines the approach followed. It can be perceived as a cascading level of technical specifications that characterize our charging problem: type of vehicle, level of charge, electricity signal price type, etc. The combination of possible choices for each dimension results in a high number of cases. In this working paper, we recall some of the load curves computed in EV-STEP to illustrate the complexity of load curve estimation and highlight the fact that the restricted set of available benchmark curves only very partially captures the range of possible load curves.
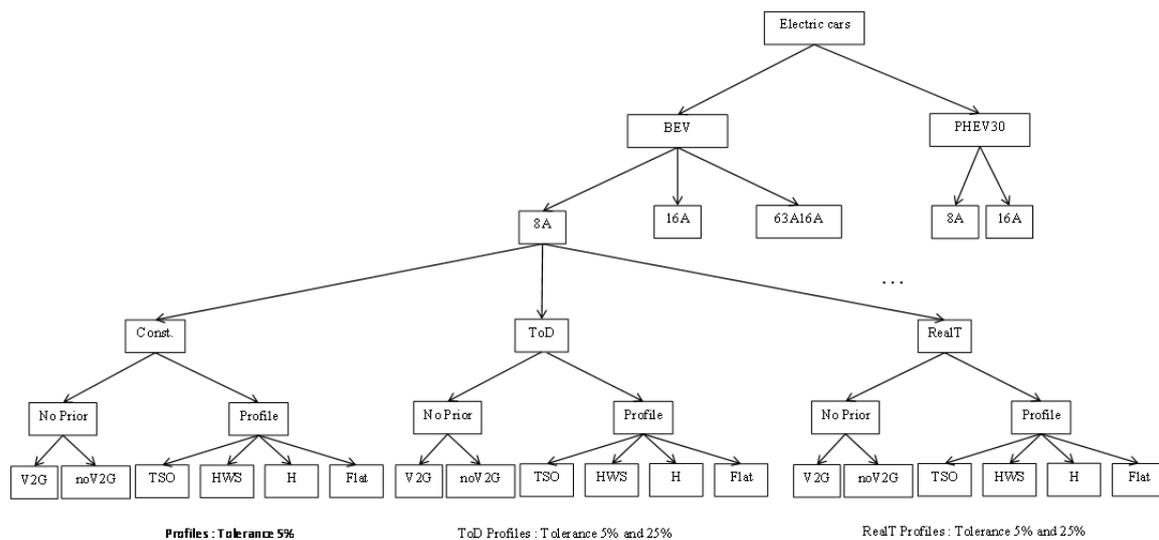
Figure 2-1. Illustration of the scenario tree

2.1.1 Effect of charging intensity and price signals

2.1.1.1 Assumptions
In this section, we consider how changes in price signals and charging infrastructure current levels affect the load profiles. Higher current levels allow a significant reduction in the charging time, while the price signal discriminates the moment of charge by its economic value. Three types of electricity price signal (Figure 2-2.2) are considered:
- A time-of-day signal (ToD): the structure of the electricity purchase price is based on the "tariff bleu" in France, which distinguishes one peak period and one off peak period. The average electricity price is 13.5c€/kWh;
- A constant price signal: One of the main advantages highlighted for electric vehicles is the low fuel cost. Yet given the expected lower "fuel" cost of electric vehicles, electric car users may not react to a ToD pricing. Thus the constant price signal (13.5c€/kWh) describes the situation where users are indifferent to daily variations of electricity price;
- A real-time price signal (RealT): here we simulate the alternative case of a totally time-dependent electricity price. Since no such tariff exists, this signal is constructed using two parameters: an average price of 13.5c€/kWh (same as the other signals), and an hourly profile calibrated from a spot price on a typical winter day.
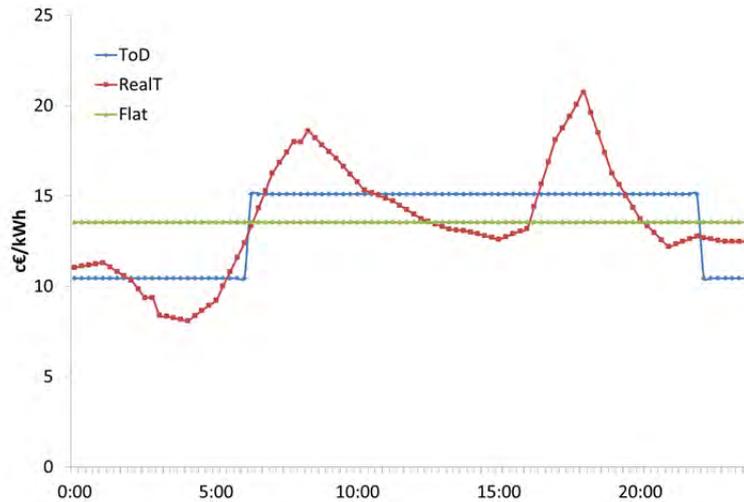
Figure 2-2. Price signal assumptions

These price signals are then further combined with three different charging levels to define 9 simulation cases:
- 8A charging current from a standard power outlet;
- 16A charging current from a dedicated wall box;
- {63A,16A} charging currents describing a fast-charging case with 2 possible discrete levels.

2.1.2 Modeling preference or cost-driven charging profiles

2.1.2.1 Assumptions

The basic solution of EV-CAP quantifies the load curve with a pure cost minimization approach. "Charging preference" here refers to prior knowledge of the charging profile expressed as a normalized envelope. This envelope is a way of including complementary information on the preferred charging period that is not related to costs. In practical terms this depicts electric vehicle car users who not only try to minimize the cost, but charge their vehicle as expressed by the secondary preference rule. However, they ignore? the cost as long as the difference in total cost is not too high. This "not too high" condition is expressed as a tolerance that becomes a parameter of the charging problem. The concept of charging profile can thus be interpreted as a preferred behavior pattern of electric car owners.

This serves as a secondary objective and modulates the load curve. The new problem formulation corresponds to a two-step optimization:
- The pure cost minimization is performed as the first objective to provide a reference cost;
- For the second optimization problem, the objective function is then to determine the lower envelope e.g. minimize the maximum power given the envelope shape constraint;
- In that case, both problems are coupled with a tolerance on the cost, and the secondary problem is constrained by the solution of the first problem.

The advantage of this double stage optimization is that load profiles remain responsive to both the price signals and the profile. The tolerance gives this cost trade-off. Hence, for a given behavioral preference, the effect of changes in the electricity price signal can be simulated. The counterpart is a more complex discrete optimization problem in which discrete charging decisions are also coupled with shape constraints. Profiles can be set to reflect various behavior patterns. The benchmark "natural" load curve for electric vehicles proposed by the French TSO is considered. Alternative rules are also simulated, such as "preferred charging distributed as time of return home" or "distributed as arrival at work, home and study place". For these two rules, the shape was calculated based on a statistical fitting with the national mobility survey. The various charging context scenarios that were then simulated are summarized in Table 2-1. For all runs of the model? a default tolerance of 5% on the total cost was applied. Complementary runs with a tolerance on 25% on the cost were also performed.
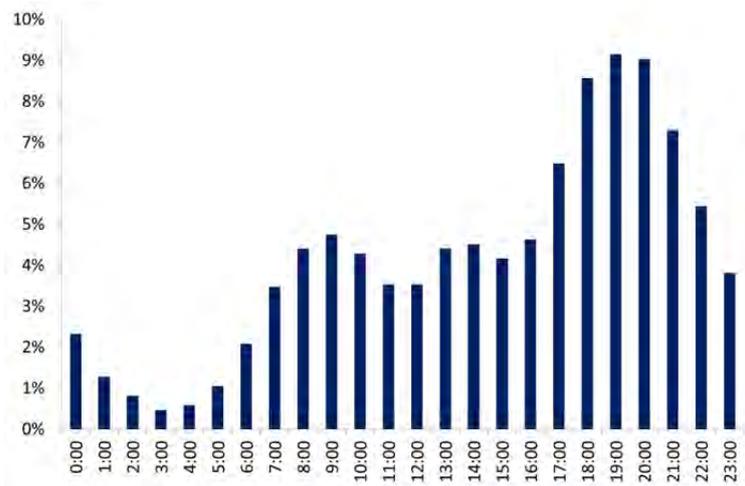
Figure 2-3. Charging profile A calibrated from: RTE (French TSO) natural charge benchmark
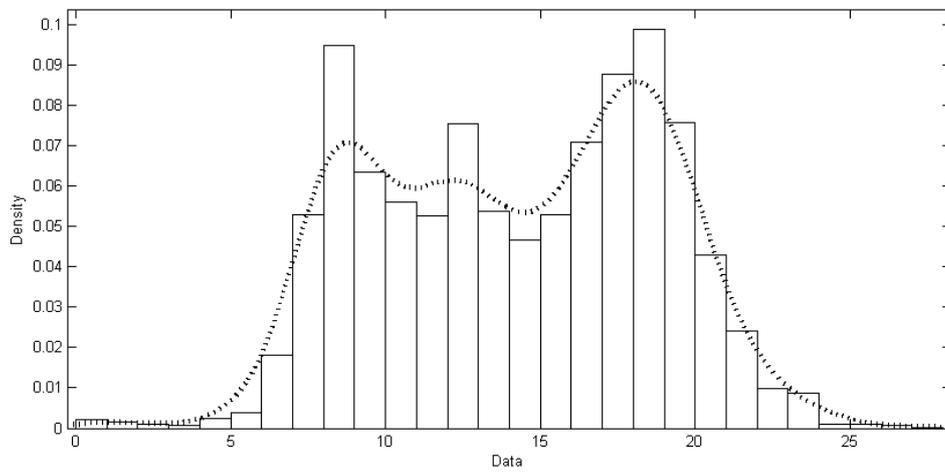

Figure 2-4. Preferred charging profile B calibrated from the rule HWS: "as hour of arrival at home, workplace and study place"
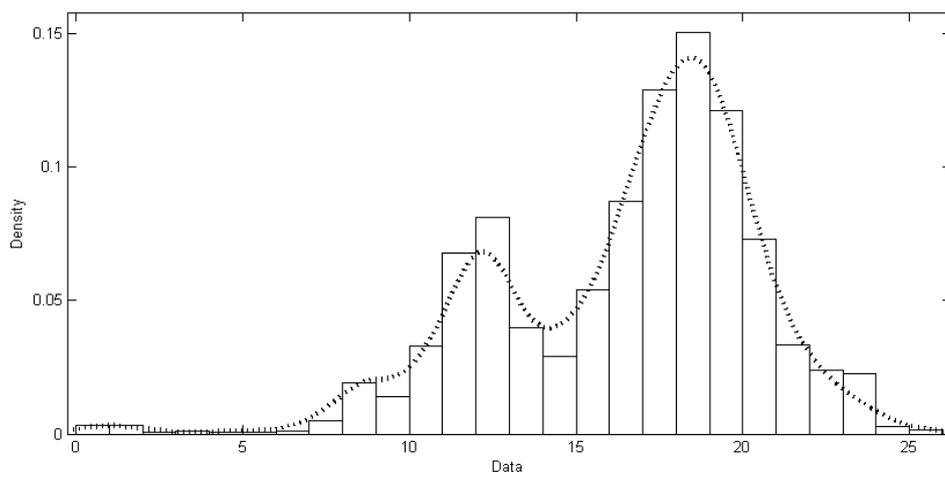
Figure 2-5 Preferred charging profile calibrated from the rule Home: "as hour of arrival at home"

Mobility profile			Charging profile characterization						Price signals	
Geographic zone	Socio econ. segment	Mobility segment	Current levels	Efficiency	SOC bounds	Preferred profile	Maximum power limit	Vehicle type	Elec. Price	V2G payment
IDF all	All	full survey	8A	0.81	SOC min=20% SOCmax=100% max number of reload event=5	TSO	Unbounded	BEV	Flat	No
						TSO			ToD	
						TSO			RealT	
						WHS			Flat	
						WHS			ToD	
						WHS			RealT	
						Home			Flat	
						Home			ToD	
						Home			RealT	
			16A,63A			TSO			Flat	
						TSO			ToD	
						TSO			RealT	
						WHS			Flat	
						WHS			ToD	
						WHS			RealT	
						Home			Flat	
						Home			ToD	
						Home			RealT	

Table 2-1.Simulated cases for the combined effect of charging current, price signal and profile

2.1.2.2 Load curves

The reason for the additional charging profile is to account for preferences that are not cost-based and differentiate solutions that would otherwise be equivalent on a pure cost basis. This is for instance clearly illustrated in the case of a constant electricity price signal where all feasible solutions are equivalent: considering additional charging profile limits the maximum power demand (Figure 2-6) between 0.7 kW/vehicle and 1.1kW/vehicle while maintaining the cost within the 5% tolerance bound.
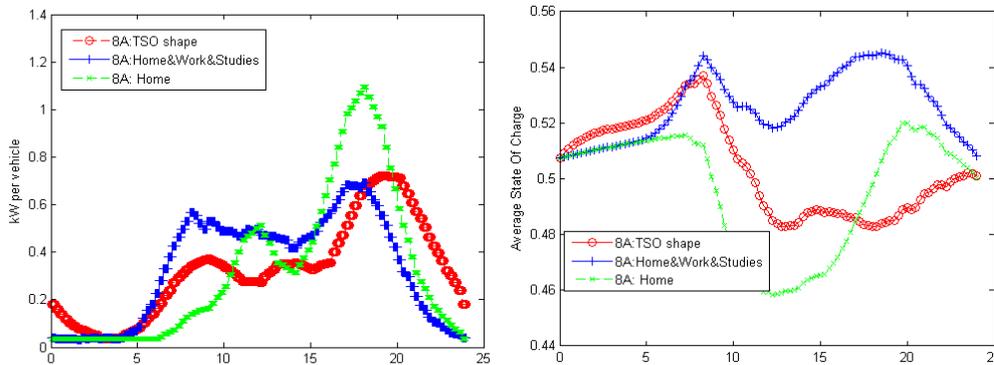
Figure 2-6. Effect of charging profiles: 8A charging

EV-CAP was then used to investigate the combined effects of economic signal, behavioral preferences and current levels.
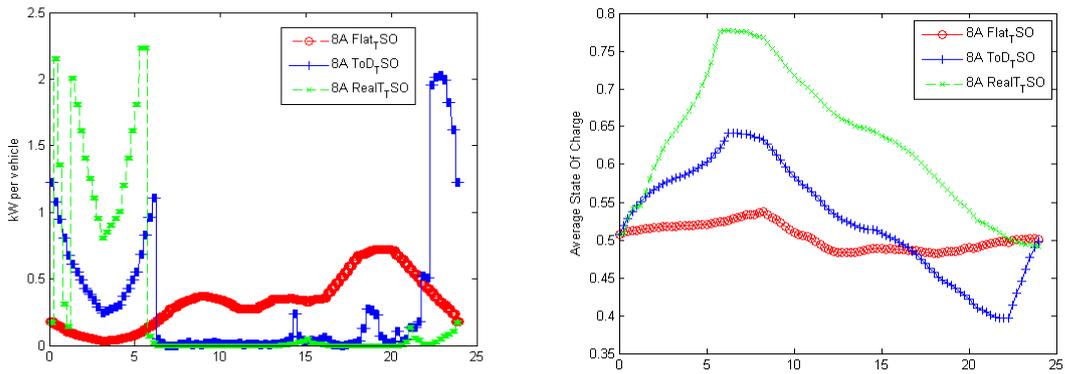
Figure 2-7. Effect of charging profiles: 8A, TSO profile and 5% tolerance on cost

With a charging current of 8A and a ToD signal, the differential cost between peak and off-peak periods remains significant and there is only a limited increase in electric demand during peak time, despite the preferred charging time profile. However, during off-peak time, several equivalent solutions exist and they are differentiated by the assumed preference. The load curve is modulated accordingly. The maximum power demand is higher at 2kW/vehicle.

When a RealT signal is considered, the economic signal and the behavioral signal tend to work in opposite ways in the morning. The minimum electricity price and least-preferred charging times both occur at around 4AM. The load curve is then adjusted to find a new allocation that leads to more fluctuation in the load profile before 6AM. During the rest of the day, the price of electricity is significantly higher and the profile has little influence on the load curve. The maximum power demand is 2.2kW/vehicle. In both cases, what is illustrated is hence the possibility to compute adjusted load curves in time periods where this adjustment follows the following rationale: respect the profile for time periods when it does not increase the total cost "too much" while maintaining the economic criteria at which the cost would otherwise be "too high".
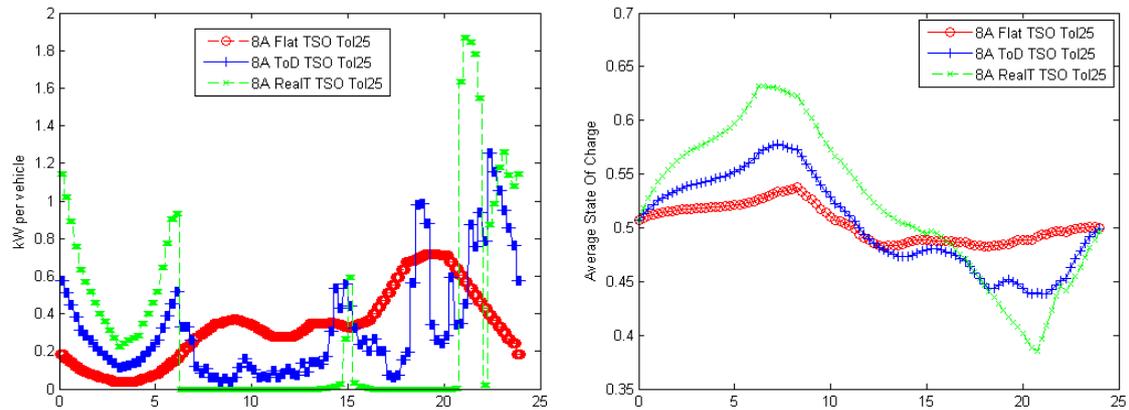
Figure 2-8. Charging at 8A, TSO profile with a cost tolerance of 25%

This is further expressed by Figure 2-8 where the tolerance on the total cost was increased to 25%. The simulated car owners are hence willing to accept a less cost optimal charging profile within this tolerance window. Consequently, charging during the day increases and the maximum power demand is reduced to 1.2kW/vehicle with a ToD price signal, and 1.9 kW for the simulated real-time pricing.
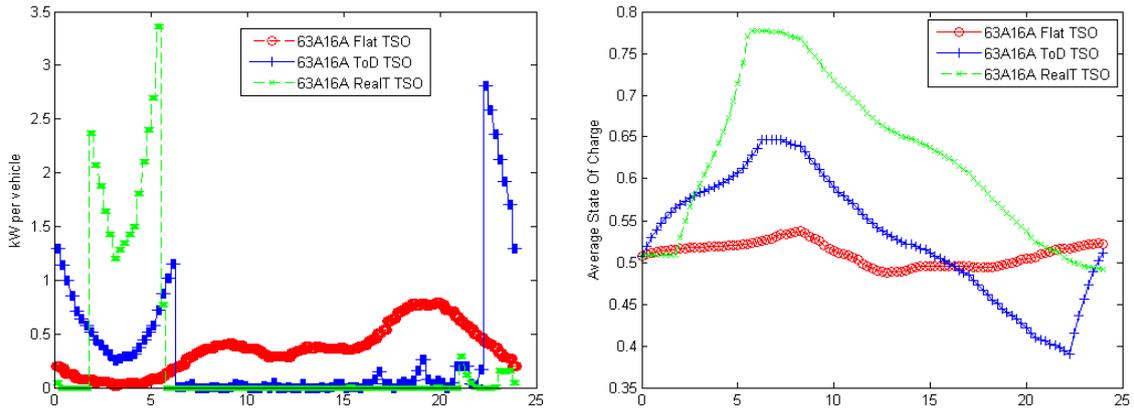
Figure 2-9. Dual mode charging at {63A,16A}, TSO profile with a tolerance of 5%
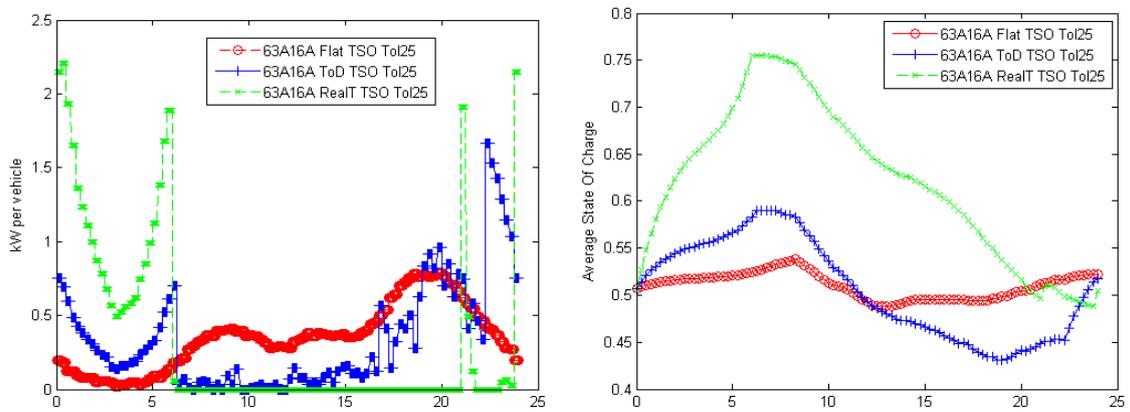
Figure 2-10. Dual mode charging at {63A,16A}, TSO profile with a tolerance of 25%

Figure 2-9 and Figure 2-10 show the load curve obtained when it is possible at each time period to select a charging level between a discrete set of choices. For a constant price signal it is still possible to limit the maximum to 0.79 kw/vehicle. For the ToD and RealT price signals, adjusted characteristic load curves are computed:

- Tolerance 5%: Max(ToD) =2.81 kw/vehicle ; Max(RealT) =3.36 kW/vehicle ;
- Tolerance 25%: Max(ToD) =1.67 kw/vehicle ; Max(RealT) =2.20 kw/vehicle ;

Profile ruleB: Arrival Work Home Study

We now consider a profile characterized by arrival times at home, workplace and study place (HWS). This shows a strong preference for daytime charging and does not strongly discriminate between night time charging periods. The morning charging preference is increased and, in the constant price case, the maximum is lowered further to 0.66 kW/vehicle for a charging current of 8A and 0.74 kW/vehicle for a dual mode charging at 63A or 16A.
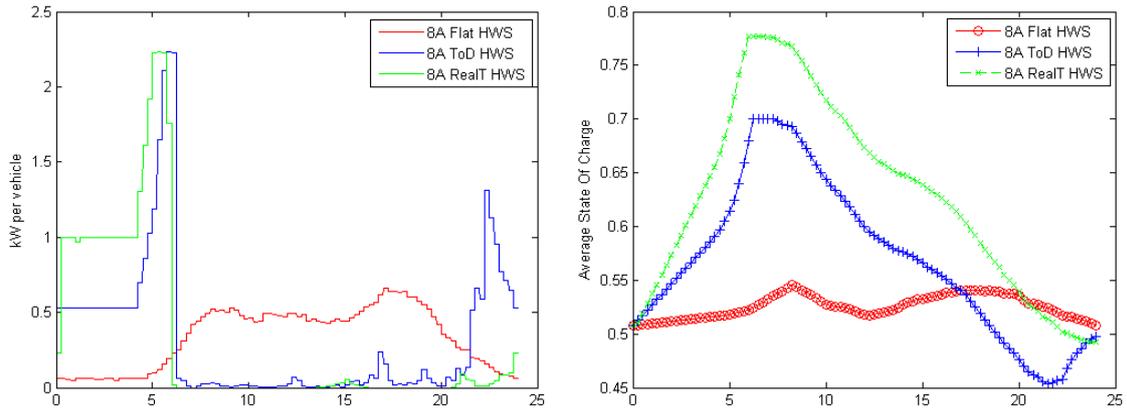
Figure 2-11. Effect of charging profiles: 8A, HWS profile and 5% tolerance on cost
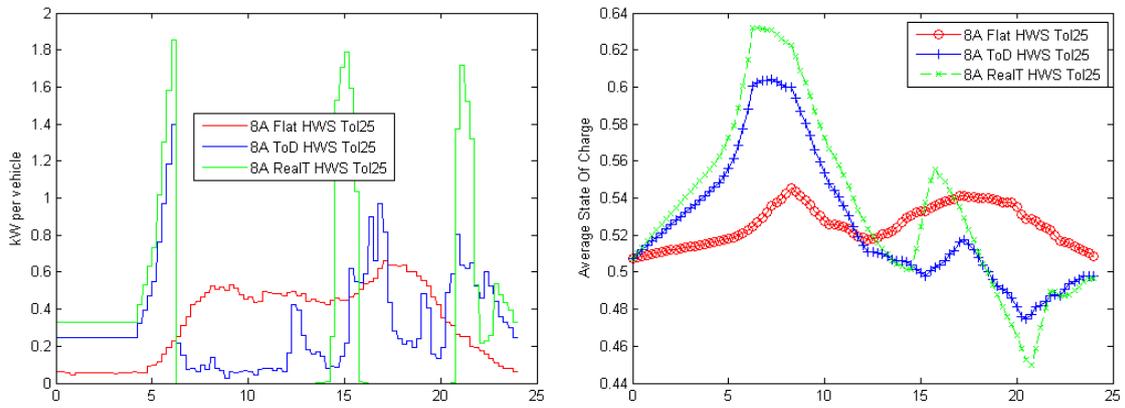
*Figure 2-12. Charging at 8A, HWS profile with a 25% tolerance on cost*
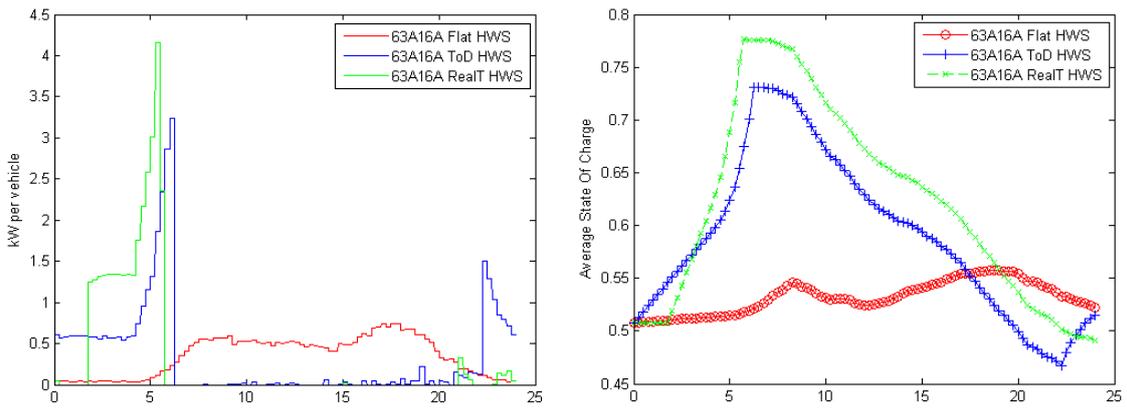
Figure 2-13. Dual mode charging at {63A,16A}, HWS profile with a tolerance of 5%
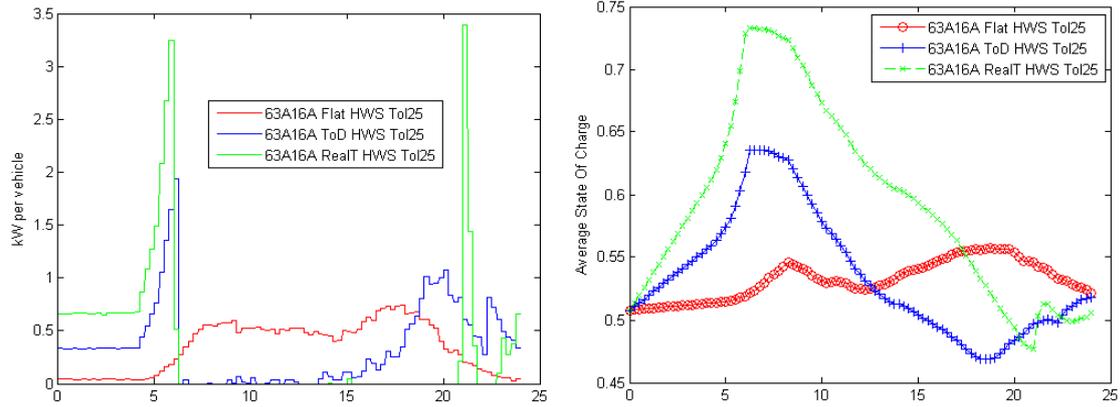
Figure 2-14. Dual mode charging at {63A,16A}, HWS profile with a tolerance of 25%

Figure 2-11 to Figure 2-14 also show the changes in the load curves when we consider the two alternative price signals and for each charging current option. The maximum loads according to the tolerance on cost are:

- 8A & 5% tol. : Max(ToD) = 2.24 kW/vehicle; Max(RealT) = 2.23 kW/vehicle ;
- 8A & 25% tol. : Max(ToD) =1.40 kW/vehicle ; Max(RealT) = 1.85 kW/vehicle;
- {63A,16A} & 5% tol.: Max(ToD) = 3.23 kW/vehicle; Max(RealT) = 4.16 kW/vehicle;
- {63A,16A} & 25% tol. : Max(ToD) = 1.93 kW/vehicle; Max(RealT) = 3.4 kW/vehicle;

Profile rule C: Arrival at Home

Finally, we consider a third profile characterized by arrival times at home only. Its distinctive features are the two peaks that reflect: a lower preference for charging in the morning, a very strong preference for charging in the evening between 6PM and 8PM, and a quickly declining preference afterwards. In this context, and assuming a constant price, the maximum load increases to 1.08 kW/vehicle for a charging current of 8A and 1.21 kW/vehicle for a dual mode charging at 63A or 16A.
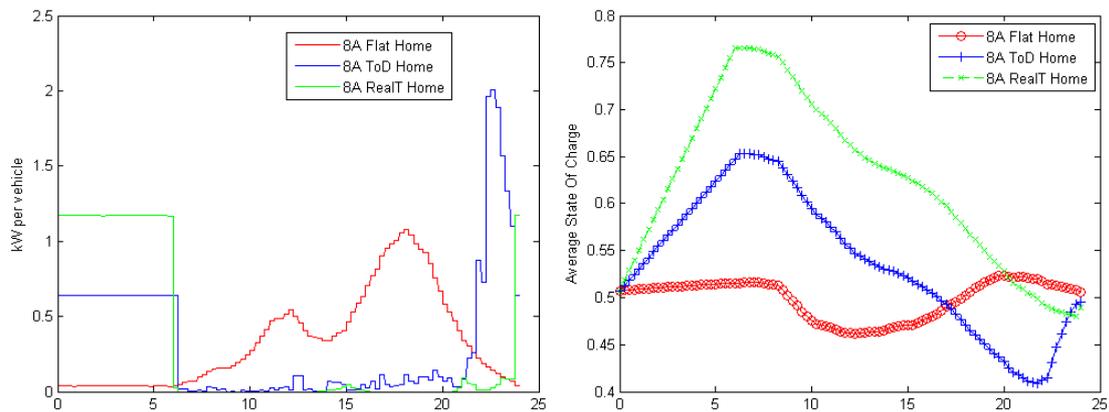
*Figure 2-15. Charging at 8A, Home profile with a 5% tolerance on cost*
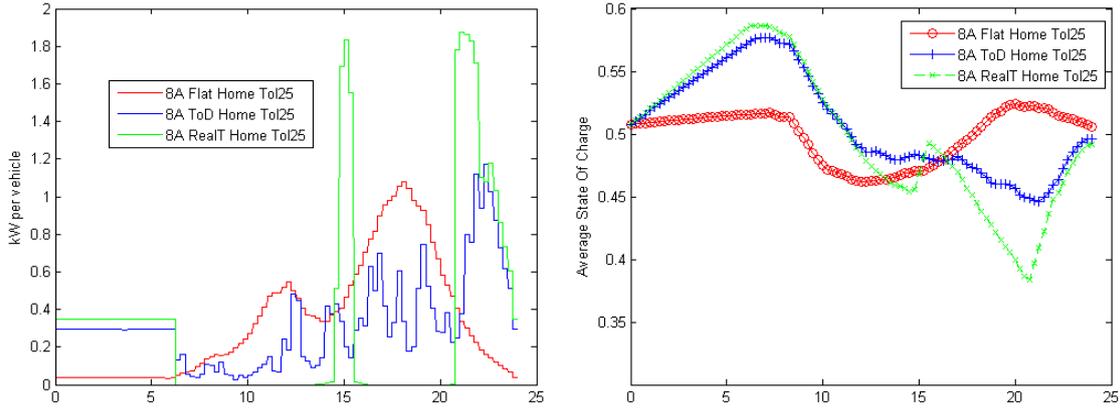
Figure 2-16. Charging at 8A, Home profile with a 25% tolerance on cost
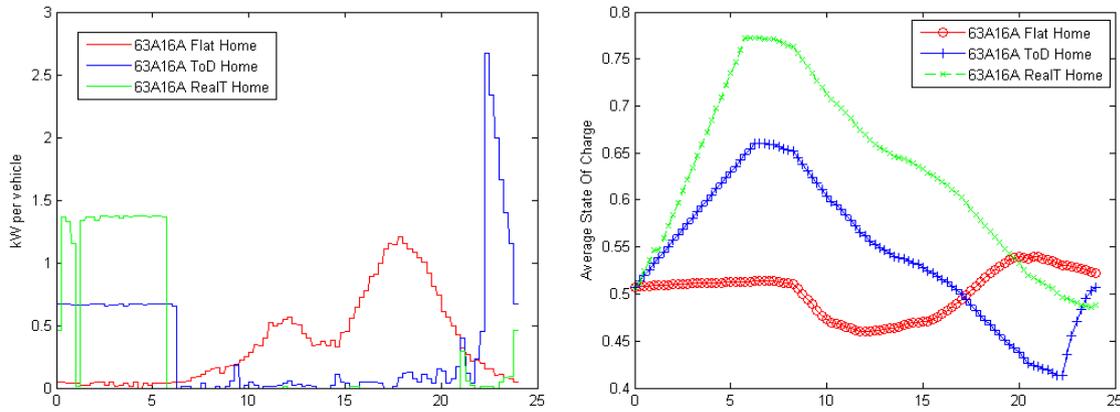
Figure 2-17. Dual mode charging at {63A,16A}, Home profile with a tolerance of 5%
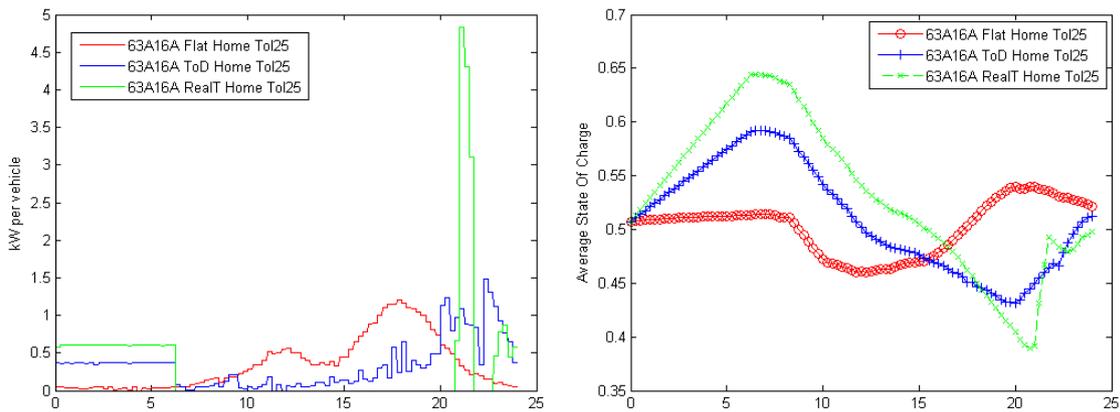
Figure 2-18. Dual mode charging at {63A,16A}, Home profile with a tolerance of 25%

Similarly, we evaluated changes in the load curves considering the two alternative price signals and for each charging current option. The maximum loads according to the tolerance on cost are:

- 8A & 5% tol. : Max(ToD) = 2.01 kW/vehicle; Max(RealT) = 1.17 kW/vehicle ;
- 8A & 25% tol. : Max(ToD) = 1.17 kW/vehicle; Max(RealT) = 1.87 kW/vehicle ;
- {63A,16A} & 5% tol. : Max(ToD) = 2.67 kW/vehicle; Max(RealT) = 1.37 kW/vehicle;

- {63A,16A} & 25% tol. : Max(ToD) = 1.48 kW/vehicle; Max(RealT) = 4.83 kW/vehicle;

2.1.3 Effect of V2G possibility

2.1.3.1 Assumptions

The most complete integration of electrified mobility in the electric system is the vehicle-to-grid operation mode, where the electricity contained in the battery can be supplied to the grid and substitute conventional power generators. While V2G is not the main operation mode for today's electric vehicles it is foreseen as a possible balancing element and should be considered in a forward-looking approach as proposed in EV-STEP. In this section, the focus is therefore on simulating such a possibility in the IDF region. , We modeled a premium for electricity supplied to the grid in V2G mode. The decision to supply electricity to the grid is then a choice between the trip schedule, the electricity purchase price signal, the V2G premium, and the available current levels. For this analysis, the RealT price signal was also used as a premium for V2G and 6 simulation cases where defined (Table 2-2).

Mobility profile			Charging profile characterization						Price signals	
Geographic zone	Socio econ. segment	Mobility segment	Current levels	Efficiency	SOC bounds	Preferred profile	Maximum power limit	Vehicle type	Elec. Price	V2G payment
IDF all	All	full survey	8A	0.81	SOC min=20% SOCmax=100% max number of reload event=5	no profile	Unbounded	BEV	ToD	Premium set as RealT price signal
									RealT	
			16A						ToD	
									RealT	
			16A,63A						ToD	
									RealT	

Table 2-2.Simulated cases group4: Vehicle to grid

2.1.3.2 Load curves

Figure 2-19 reports the calculated load curves and average state-of-charge of the fleet when the electricity price signal is of a ToD type. The owner can charge with a ToD price signal and supply electricity to the grid with a RealT signal (accounting for the efficiency). The global strategy is then to increase the state of charge to the maximum during off-peak periods in order to ensure both trip demand and supply to the grid when they are economically advantageous. For a charging current of 8A, the time it takes to fully charge the battery is important, and the load will remain at around 2 kW/vehicle during the off-peak time with a maximum of 2.21 kW/vehicle. For higher charging currents, there are multiple equivalent solutions during the off-peak period as less time is required to charge the batteries. The maximum loads are then 4.22 kW/vehicle and 10.37 kW/vehicle for a 16A charging current using fast charging.

Taking into account the efficiency of the charger, the V2G mode is only activated when both the premium and state of charge are sufficiently high. The maximum power supplied back to the grid is 3.3 kw/vehicle. As it is more cost-optimal to supply electricity to the grid when the premium is at its highest, the length of the two discharge period varies. Furthermore, this price asymmetry in the RealT signal leads to the coherent observation that when the current level is low (8A), the electricity supplied to the grid is preferentially reduced in the morning.
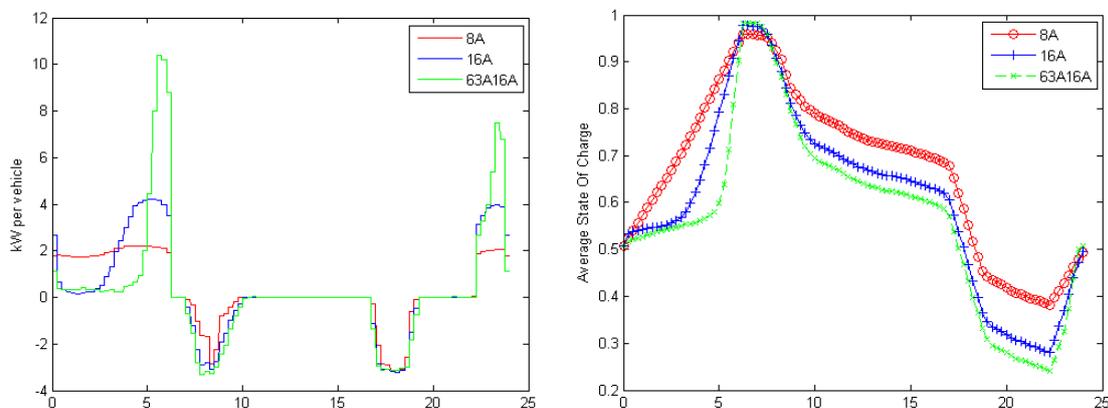

Figure 2-19 Load curve in a V2G mode with a ToD electricity purchase signal
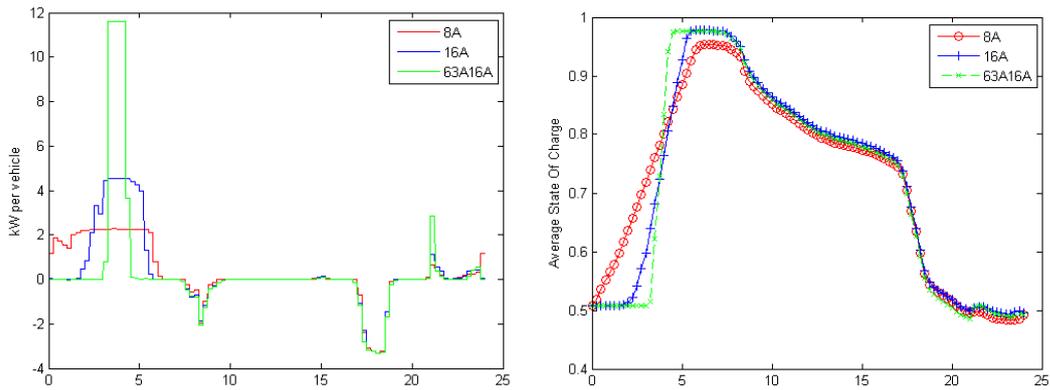
Figure 2-20. Load curve in a V2G mode with a RealT electricity purchase signal

Figure 2-20 now describes the load curve in the case of a RealT price signal for both the electricity purchase and V2G premium. One main charging event takes place in the morning with a duration that depends on the charging current level. The maximum load is then 2.27kW for an 8A charging current, 4.54 kW for a 16A charging current and 11.60 kW when fast charging is available. The supply of electricity to the grid is limited in the morning (the maximum power supplied is still 2kW/vehicle) but using the V2G mode provides up to 3.31 kW/vehicle in the evening.

2.1.4 Effect of electric vehicle type

2.1.4.1 Assumptions

All of the characteristic load curves described so far were calculated for pure battery electric vehicles. We consider here additional simulations in order to characterize the electric load curves in a plug-in hybrid vehicle (PHEV) configuration. A PHEV30[2] mode was thus simulated, defined by a lower battery capacity (10kWh) and a reduced consumption of electricity per km driven (33% share of electric energy).

Vehicle type	Consumption		Battery ca-pacity	Split-up into electricity and conventional propulsion	
	electrical (kWh/km)	conventional (l/100km)	(kWh)	electrical (%)	conventional (%)
BEV	0,13-0,25	0,0	25-35	100	0
City_BEV	0,12-0,16	0,0	10-16	100	0
PHEV90	0,15-0,25	7,5	12-18	66,6	33,3
(PHEV30)	0,15-0,25	7,5	6-12	33,3	66,6

Table 2-3. Consumptions of Electric vehicles from the G4V project (Parameter manual)

The charging conditions of the PHEV30 cars are also modified. In a BEV configuration each vehicle is returned at its initial state of charge (different among vehicles) at the end of our simulated representative day. In a PHEV30 configuration, the minimum state of charge for each vehicle at the end of the horizon is a random number that varies between the minimum and the initial state of charge (Figure 2-21). The maximum number of charging events per car is also modified from 5 to 3. This assumption translates the fact that PHEV users are potentially less willing to charge their car very often. Furthermore, to limit the number of cases, fast charging is not considered for PHEVs and only the no-behavioral and TSO profiles are simulated in this analysis: the resulting 12 new cases are summarized in Table 2-4.

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2 From the G4V project
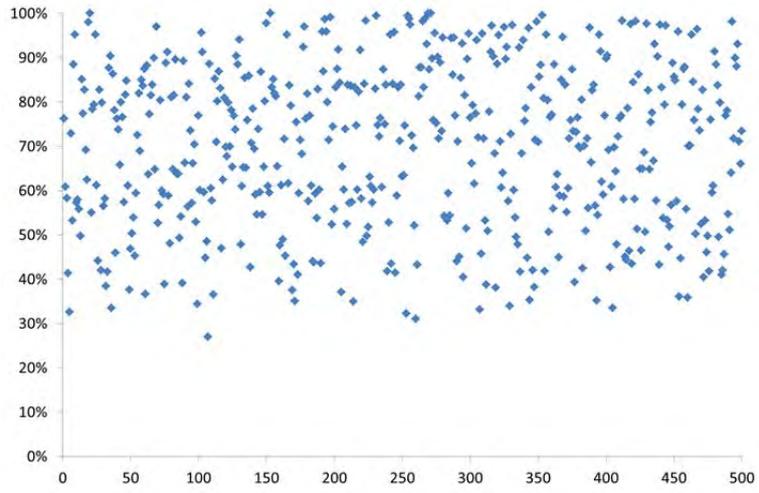
Figure 2-21. Final SOCs expressed as a percentage of the initial SOC in the PHEV30 mode

Mobility profile			Charging profile characterization						Price signals	
Geographic zone	Socio econ. segment	Mobility segment	Current levels	Efficiency	SOC bounds	Preferred profile	Maximum power limit	Vehicle type	Elec. Price	V2G payment
IDF all	All	full survey	8A	0.81	SOC min=20% SOCmax=100% max number of reload event=5	no profile	Unbounded	PHEV30	Flat	No
									ToD	
									RealT	
						TSO			Flat	
									ToD	
									RealT	
			16A			no profile			Flat	
									ToD	
									RealT	
						TSO			Flat	
									ToD	
									RealT	

Table 2-4.Simulated cases group5: Vehicle type

2.1.4.2 Load curves

Charging intensity and price signals
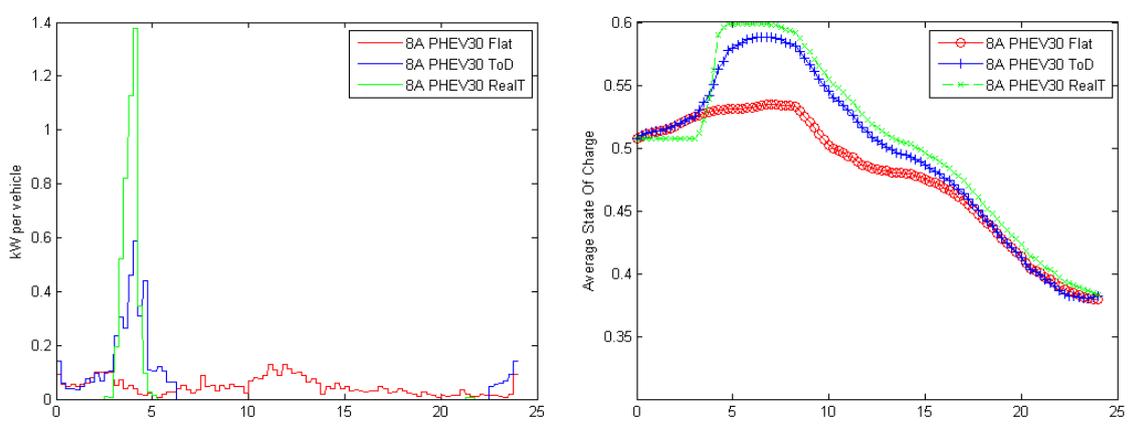
Figure 2-22. Load curves and average states of charge for a charging current of 8A: PHEV30
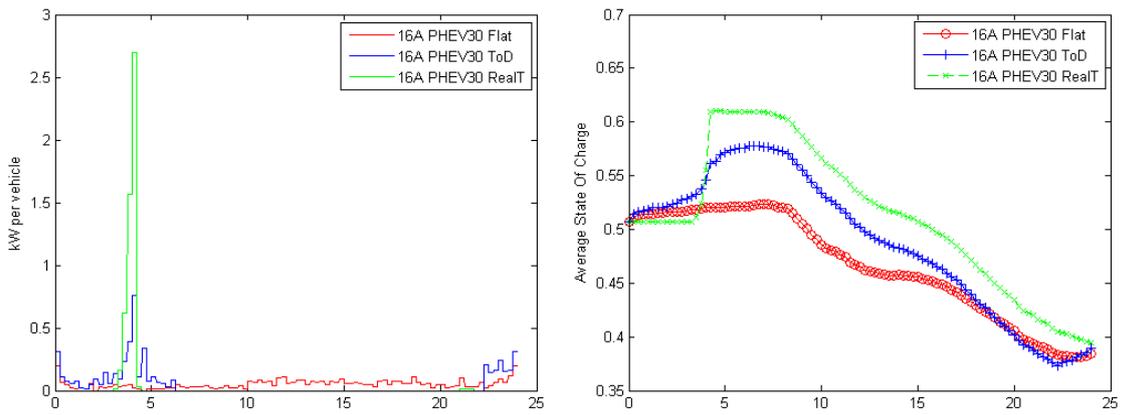
Figure 2-23. Load curves and average states of charge for a charging current of 16A: PHEV30

Figure 2-22 and Figure 2-23 depict the 6 load curves characterized for a PHEV30 when the sole objective is cost minimization. The maximum loads are significantly reduced:

- 8A: Max(Flat) = 0.13 kW/vehicle; Max(ToD) = 0.58 kW/vehicle; Max(RealT) = 1.38 kW/vehicle ;
- 16A: Max(Flat) = 0.20 kW/vehicle; Max(ToD) = 0.76 kW/vehicle; Max(RealT) = 2.70 kW/vehicle ;

<u>Profile rule A: TSO</u>
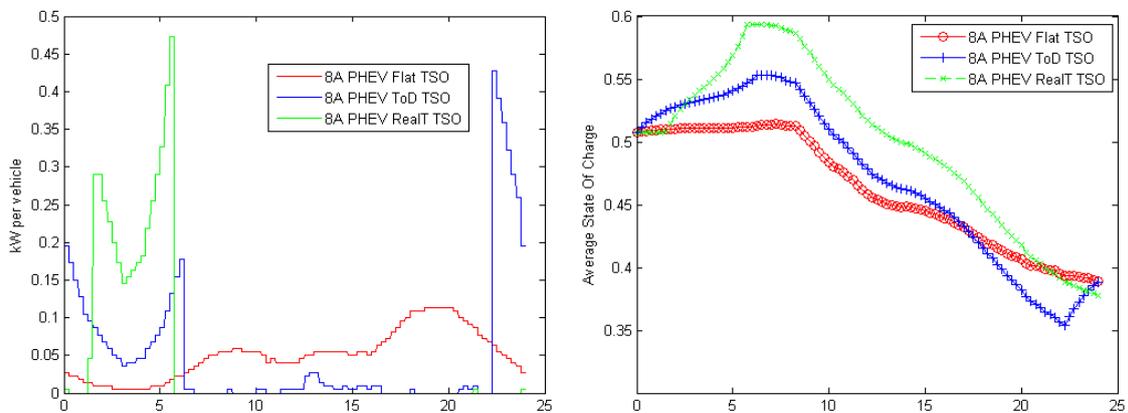
*Figure 2-24. Load curves and average states of charge: 8A/ PHEV30/ profile TSO*
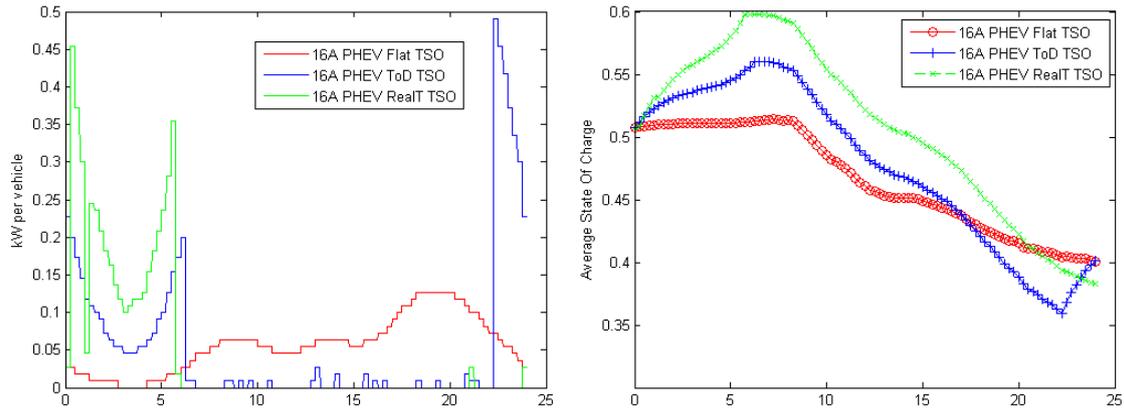
Figure 2-25. Load curves and average states of charge: 16A/ PHEV30/ profile TSO

Figure 2-24 and Figure 2-25 then show the 6 load curves characterized for a PHEV30 when a TSO-type profile is considered. The maximum loads are further reduced:

- 8A: Max(Flat) = 0.11 kW/vehicle; Max(ToD) = 0.43 kW/vehicle; Max(RealT) = 0.47 kW/vehicle ;
- 16A: Max(Flat) = 0.13 kW/vehicle; Max(ToD) = 0.49 kW/vehicle; Max(RealT) = 0.45 kW/vehicle ;

2.2 Impact on the load profile in Ile-de-France

In section 2.1 several electric car load profiles were defined for various assumptions of the vehicle charging problem. Each computed load curve reflects a particular EV-user context, where the emphasis is either on charging current level, price signal or behavior priority? The key idea was to quantify the variability in load curves and the necessity to consider more than a single or a couple of benchmark curves. A complementary concern that stems directly from the chronology of the electric power demand for electric cars is the impact on the existing load curve.

We consider this issue here based on the existing load curve for the Ile de France region without electric vehicles. Although this reference load curve without electrified mobility could also be modified in the future, transformations of the load profiles of other electric usages were not modeled in the EV-STEP project. Figure 2-26 illustrates the daily variation of average electricity demand over a year for the Ile de France region and its upper and lower bounds. It shows the typical weekly and seasonal pattern of electricity consumption. Figure 2-27 complements this view with the hourly load for a typical winter day.

The load impact of electric cars is then computed against this reference daily load pattern. Electromobility development targets for 2030 for the Ile de France region as a whole are very ambitious and aim at 350 thousand vehicles in 2025 and 1million3 vehicles in 2030.

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3 To be compared to a stock of just 36,000 electric cars in France in 2014.
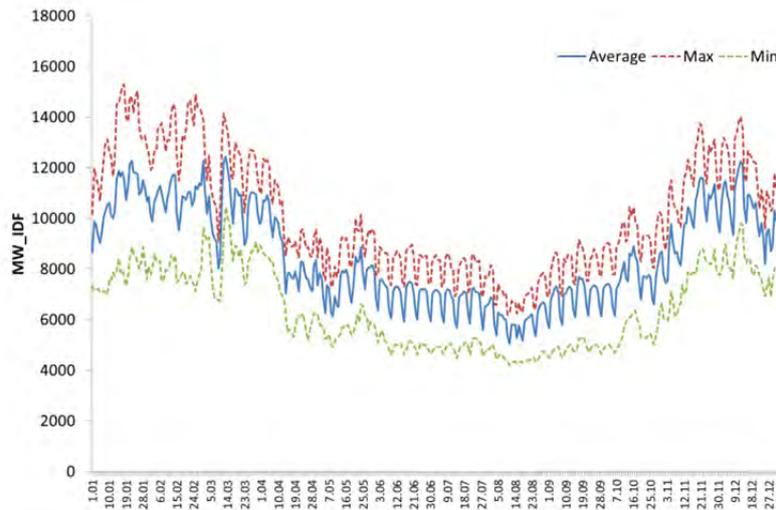
Figure 2-26. 2013 electric load in the Paris Ile de France Region: data from RTE (French TSO)
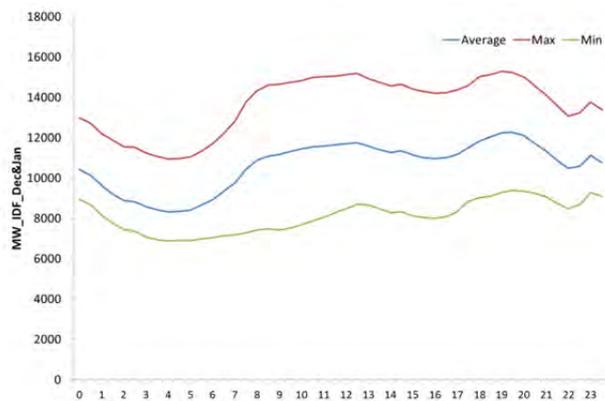
Figure 2-27. Daily electric load curve for the Paris Ile de France region (December January average): data from RTE (French TSO)

2.2.1 Impact of individual characteristic curves on the IDF load curve

The impact on the global load curve can be estimated by scaling up a characteristic load curve with the anticipated number of electric cars. Figure 2-28 features an illustration for 3 of the cases analyzed above and for pure electric vehicles. It shows the time-of-day pricing scheme's capacity to avoid charging EVs during the current evening peak. Extrapolating this effect for 1 million vehicles partially fills the night time "valley" but also brings the 10 PM peak to the level of the current 7 to 8 PM peak. The impact of a generalized vehicle-to-grid possibility is considerable, with an effective shift of consumption from peak time to valley time. The overall shape of the load curve is significantly modified. However, extrapolating this situation to 1 million cars reveals a limit in the positive contribution of a generalized V2G capability since new peaks and new valleys are formed.
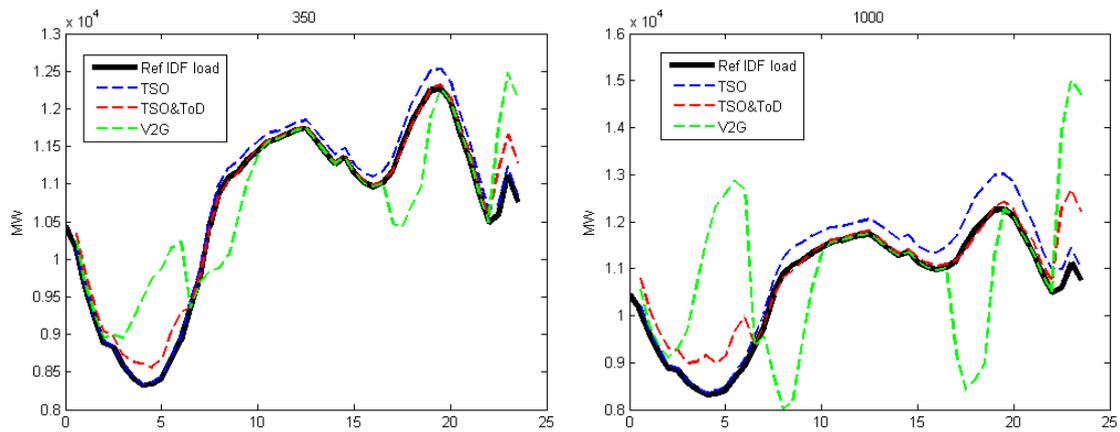
Figure 2-28. Generalized impact from selected characteristic load curves: 350 thousand and 1 million electric cars

2.2.2 Case mixer

We then propose a "case mixer" as a simulation tool for further load curve impact analysis. The starting point is that each isolated case represents the characteristic load curves for a given context. Yet in the future, electric car fleets will most likely feature a mix of charging contexts, preferences and vehicle types. A mixing approach is thus natural to represent more complex impacts of EVs on the existing electricity demand while using the same knowledge database of isolated cases. It combines individual load profiles based on user-specified shares of drivers that adopt a given charging profile. Its main advantages are to simulate heterogeneous contexts in a flexible way, and to avoid rerunning the MIP optimization engine. An interface was developed to facilitate this process with shares allotted according to 6 dimensions: current level, price signal, behavior profile, cost tolerance, V2G mode, and the share of BEV and PHEV30.
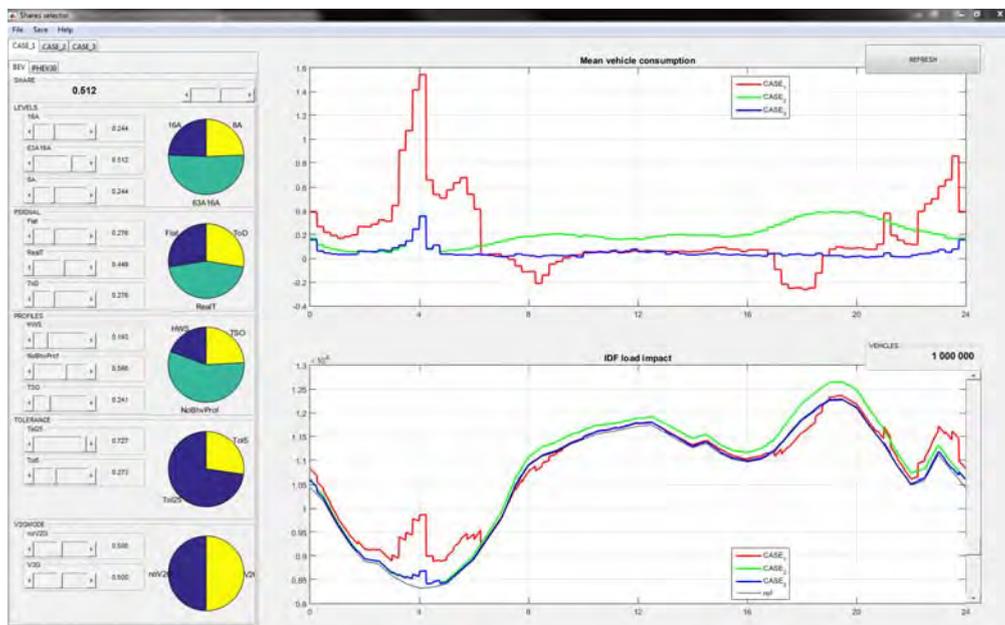
Figure 2-29. User interface for the case mixer

Share of EV users in each case	Levels	Scen1	Scen2	Equiprob
Levels	8A	45%	45%	33%
	16A	45%	45%	33%
	{63A, 16A}	10%	10%	33%
Price signals	Flat	90%	60%	33%
	RealT	5%	10%	33%
	ToD	5%	30%	33%
V2G mode	NoV2G	80%	80%	50%
	V2G	20%	20%	50%
Vehicle type	BEV	90%	90%	50%
	PHEV30	10%	10%	50%
Profile	No profile	5%	20%	33%
	TSO	80%	40%	33%
	HWS	15%	40%	33%
Tolerance on cost	25%	80%	80%	50%
	5%	20%	20%	50%

Table 2-5. Case mixer scenario definition
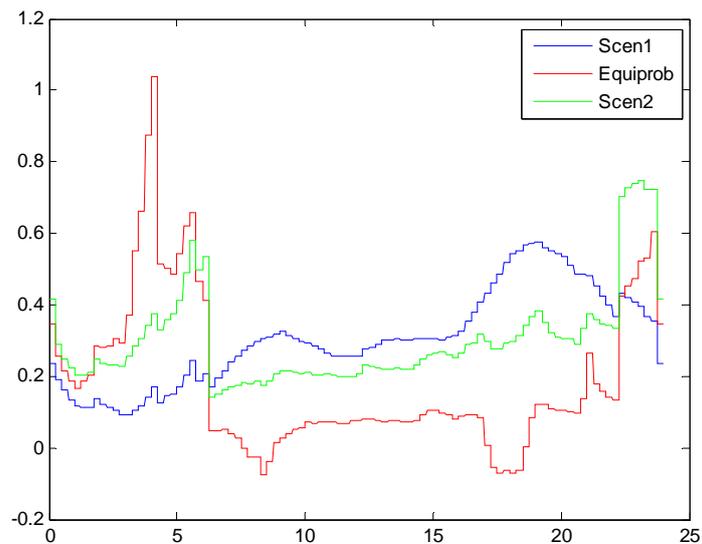
Figure 2-30. Equivalent characteristic load curves for the three scenarios
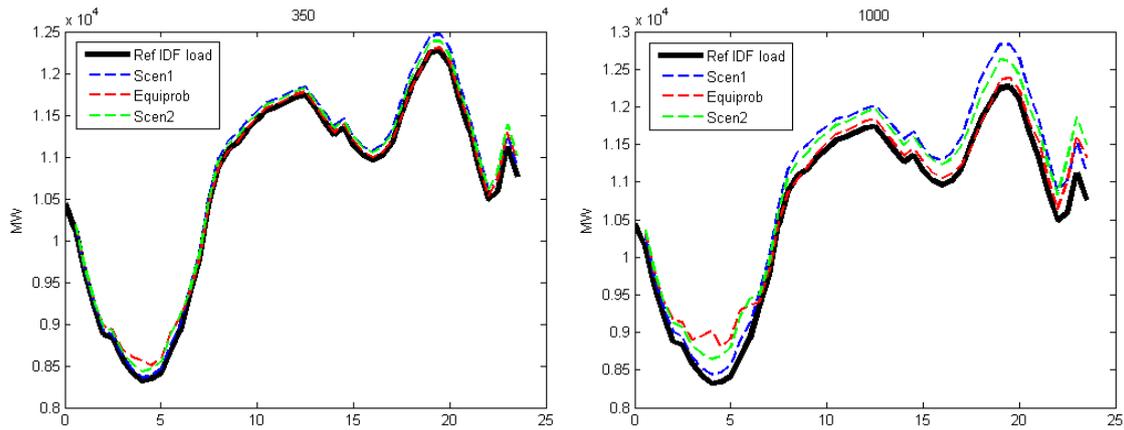
Figure 2-31. Estimated impact from the three aggregated scenarios

We then defined three case studies among the various possibilities (Table 2-5) and simulated them to illustrate this possibility. The characteristic load profiles for a representative vehicle as well as the impact on the global electric load curve are reported in Figure 2-30 and Figure 2-31. In "Scen1" most of the fleet is charged according to the time of arrival at home and work, the cost of charging is perceived as constant, with most charges at low current levels. In "Scen2", a higher share of EV users considers a price structure of a time-of-day type, and a higher share of drivers do not charge according to behavior profile, but seek only cost optimization. Finally, in "Equip" the shares are balanced in each category. These less homogenous settings yield original load profiles with a more balanced impact on the existing load curve (compared to Figure 2-28). The potential increases of the evening peak power demands caused by a fleet of 1 million vehicles are 4.5% for "Scen1", 3.1% for "Scen2" and only 1.4% for the "Equip" case. In the latter case and for 1 million vehicles equally distributed between BEV and PHEV30, V2G provides flexibility by filling the night time valley without significantly augmenting the evening peak.

2.2.3 Extension for geographic distribution of load

Through the previous steps, we computed the total charging cost, the load impact in kW, and the state of charge for the prospective fleet and for each individual vehicle. The purpose of the "Attribution" step is then to propose an initial geographical distribution of the load curve impact by a specification of its disaggregation by localization or parking types. This is done using the statistical analysis of the mobility survey. In particular, three criteria are characterized: the zone of destination, the trip purpose, and the type of parking. We consider here the destination of each trip and hence the location of the vehicle at each time step. This distribution is then simply used to split the load curve by trip purpose. This view highlights the challenges of efficiently developing charging at the work place.
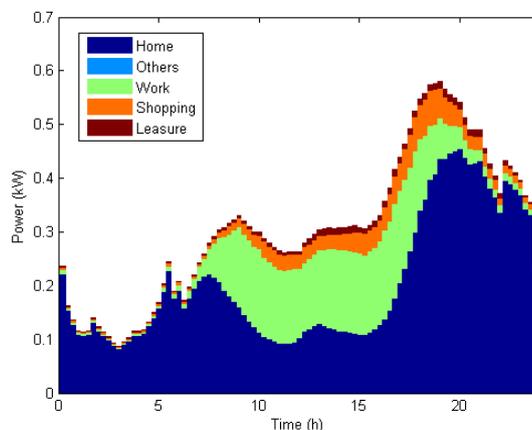

Figure 2-32. Charging and distribution by location

2.3 Conclusion

In this document we summarize the main findings of the local case analysis performed for the Ile de France region as part of the EV-STEP project. We focused on the specific issue of future charging strategies and their impact on the electric load curve. The load profiles simulated and discussed aim to improve understanding of this issue by highlighting some of the mechanisms involved with a low time granularity of 15mn: mobility demand, charging current, price signals, behavior priority, cost tolerance, vehicle-to-grid, etc. In particular, this approach explores which mechanisms can generate different charging profiles from those proposed as a benchmark today.

The EV-CAP platform was defined as a theoretical optimization environment developed for such an analysis. It has allowed the flexible simulation of several charging contexts. A robust conclusion is that simplistic benchmark profiles provide a very partial understanding of the potential impact of electric vehicles on the current load profiles. Some insights from the investigated load:

- While the maximum load from the current benchmark is commonly estimated at 0.7 kW/vehicle, our calculated load curves show that for different pricing mechanisms and assumptions on the economic or behavioral rationale of drivers (including V2G option) this maximum could vary significantly.

- Simulations with a real-time pricing mechanism also show that control via price is only partially beneficial as it can lead to a concentration of charging decisions even when behavior priorities are assumed. This is more the case when higher charging currents are available.

- Implementing a V2G mode allowed us to illustrate how V2G can induce original strategies that modify the overall shape of charging profiles with higher demand when the vehicle is in charge mode at around 2kW per vehicle but with a potential decrease in the peak load in a supply-to-grid mode of -3 kW per vehicle.

Finally, a case mixer approach was proposed to weight and combine the different case studies in order to provide an estimation of the load curve impact for drivers in heterogeneous charging contexts. As each single optimization step could take several hours, the mixer as two benefits: it uses the knowledge obtained from individual runs, and it depicts a more heterogeneous situation in which different decision environments coexist. For the Ile-de-France region, this was illustrated for hypothetical shares.

These results increase the understanding of the electric vehicle challenges at local scale. Yet the modeling work and analysis proposed here did not cover several local issues. These are proposed below as possible leads for further research:

- The statistical analysis of mobility behavior was performed for niche mobility markets (specific markets such as the 20% most mobile or the 20% least mobile car users) but the load profiles for such specific mobility groups were not computed. Changing the basis used for the initial mobility analysis to isolated could constrain the available charging period and thus the load curve for this group of users;

- The socio-economic information contained in the mobility survey was not fully exploited. A differentiation by revenue or activity group could provide a valuable extension of the insights proposed here;

- The potential for load displacement among districts was not treated. This is a natural extension of the geographic distribution where it could be interesting to investigate cases of "electricity trade" by vehicle movements;

- To limit the number of cases to a reasonable number, the influence of some of the charging parameters such as charging efficiency or the maximum number of reloads was not fully investigated;

- Other electricity price signals could be imagined. For instance, a higher share of variable renewables, such as solar power, could justify a price incentive to charge during the day.

References

[1] RTE, "édition 2011 Bilan Prévisionnel de l'équilibre offre-demande d'électricité en France". 2011.

[2] D. Ile-de-France, "L'approvisionnement énergétique du Grand Paris (séminaire du 25 novembre 2013)", 2014. [En línea]. Disponible en: http://www.driee.ile-de-france.developpement-durable.gouv.fr/l-appovisionnement-energetique-du-r932.html.

[3] G. Pasaoglu, D. Fiorello, L. Zani, A. Martino, A. Zubaryeva, y C. Thie, "Projections for Electric Vehicle Load Profiles in Europe Based on Travel Survey Data". 2013.

[4] Direction Régionale et Interdépartementale de l'Équipement et de l'Aménagement Ile-de-France, "Enquête globale transport: Motorisation et usage de la voiture en Île-de-France". 2013.

[5] François Bertrand, Christine Couderc, y Éric Ladegaillerie, "Les cahiers de l'Enquête Globale de Transport: La dynamique des activités en Ile-de-France". 2008.

[6] OMNIL, "Enquête globale transport: La mobilité en Île-de-France". 2012.

[7] Commissariat général au développement durable, "La mobilité des Français : panorama issu de l'enquête nationale transports et déplacements 2008". La Revue du CGDD, 2010.

[8] "Enquête nationale transports et déplacements (ENTD) 2008 [Sources et Méthodes, Opérations statistiques et production d'indices, Transports] : Observation et statistiques", 2015. [En línea]. Disponible en: http://www.statistiques.developpement-durable.gouv.fr/sources-methodes/enquete-nomenclature/1543/139/enquete-nationale-transports-deplacements-entd-2008.html.

[9] RWTH, "G4V project - Parameter Manual". 2010.

[10] Charles Botsford, Adam Szczepanek, "Fast Charging vs. Slow Charging: Pros and cons for the New Age of Electric Vehicles", *EVS24 Stavanger, Norway*, 2009.

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