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Optimization model and economic assessment of collaborative charging using Vehicle-to-Building

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ABSTRACT

Electric vehicles and plug-in hybrids are gaining popularity on the personal transportation market. These vehicles store energy that is unused when parked. This distributed energy source can therefore be used to provide ancillary services such as grid regulation or spinning reserves, but also for demand-side management. In this paper, we are proposing the concept of *collaborative charging* in the context of Vehicle-to-Building, where the vehicle and building operators engage themselves into a synergistic relation, with vehicles freely charged in exchange for shaving power peaks of buildings. For that purpose, simulations of vehicle fleets are conducted, with the charging schedule optimized by a linear programming model that is applied to manage the electric demand of a suburban university campus. These simulations, made in the context of a regulated electric market, demonstrate that collaborative charging can be financially viable for both the institution hosting the system and the participants.

1. Introduction

The deployment of electric vehicles (EVs) is a major trend in today's personal transportation market. Hybrid vehicles have become a sizable portion of the number of cars driven and their evolution involves the possibility to recharge them with enhanced battery capacity. Likewise, pure EVs are gaining market shares and this trend is rising.

But is the power grid able to sustain a massive adoption of EVs? In 2007, it has been estimated that the conversion into EVs of up to 84% of the vehicles in the U.S. can be supported by the existing power grid, assuming that these vehicles will be charged through some valley-filling charging methods (i.e., charging off-peak in order to maintain a flat power demand over the whole day) (Kintner-Meyer, Schneider, & Pratt, 2007). But valley-filling charging is not obviously achieved in practice, such that a significant shift toward EVs combined with a disorganized charging would constitute a stress for the grid, creating overload issues at peak times (Clement-Nyns, Haesen, & Driesen, 2010).

Organizing charging of EVs is thus required, in order to spread the load over the day while ensuring that cars are properly charged for the needs of their owners. Moreover, the electronic and charging systems of EVs can be designed to interact with the grid in a bidirectional manner (a.k.a. Vehicle-to-Grid or V2G) to alleviate the expected negative effects of their presence and even provide an enhancement to the grid (Kempton, Tomić, Letendre, Brooks, & Lipman, 2001). It is therefore not surprising that industry leaders are investigating the potential, the challenges, and the possible outcomes of the deployment of a smarter grid where EVs would not just be an additional load (Schewel, Brylawski, Chan-Lizardo, & Lovins, 2008).

In this study, a bidirectional relationship is simulated at a smaller scale, at a building or campus level with a power-constrained grid, where a substantial fraction of the electricity bill will be determined by the cost of the peak power consumption of the building or campus grid ($/kW), in addition to energy cost ($/kWh). The Vehicle-to-Building (V2B) concept was introduced in 2008 (Schewel et al., 2008) as a subclass of the V2G idea, where EVs would exchange electrical energy with a building and provide demand-side management features to optimize the building energy consumption (Benetti, Caprino, Della Vedova, & Facchinetti, 2016; Gelazanskas & Gamage, 2014). V2B has the same implications as V2G in terms of hardware needed and synchronization between the agents involved, but at the community level. Moreover, V2B should be easier to deploy due to its smaller scale and thus be achievable before V2G.

Vehicles in working place parking lots are traditionally in a standby mode from arrival in the morning to departure in the

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afternoon or evening. For rechargeable plug-in hybrids or EVs, that could mean a formidable amount of energy sleeping right next to an avid energy consumer such as a building, a university campus, a hospital, etc. With a smartless infrastructure for recharging these vehicles, the worst case scenario is a mass demand in the morning when vehicles arrive within a short period of time, creating or accentuating a peak in the power demand. Smart charging stations that avoid charging when the grid is overloaded already exist and can distribute the load over a long period, so that the grid does not suffer from excessive punctual demand. However, it would be even better to charge the vehicles when the power demand is low and use their energy capacity to prevent peak energy demands. A building or a campus using such a strategy will allow the power component of its electricity bill to be reduced by capping the peak power demanded on its connection to the utility company. Eventually, V2B may even enable the building or campus to reduce their power requirements.

In the scope of this study, we intend to create a win-win situation that we refer to as *collaborative charging*, where the vehicle owner will have his vehicle recharged for free in exchange for providing the parking lot owner (e.g., building, university, hospital) with the control of the energy contained in his vehicle battery. Doing so, the institution will benefit from an energy reserve it can use to lower its power peaks and thus its electricity bill.

In this paper, linear programming optimization is applied to a system model to produce an optimal decision sequence, a schedule of whether vehicles should charge, discharge, or standby for each of the time steps during which they are plugged into a smart, bidirectional charging station in the parking lot. Using the power consumption profile of a university campus for the year 2011 as the input for our model, the output of linear programming will generate a power profile optimized with a reduced electricity costs. In essence, the V2B feature of the plugged-in vehicles will enable the reduction of the excess power peaks. The results of this optimization will be compared to the actual cost of energy for a given campus and demonstrate the financial viability of V2B.

In addition to the proposal of the collaborative charging concept, two main contributions stem from this paper. First, we are proposing a realistic model for simulating collaborative charging, a model which can be optimized through a convex optimization method. This model is a baseline for evaluating collaborative charging approaches, allowing the evaluation of the extend to which the results of scheduling methods are working online in comparison to those obtained with our model, which is providing the optimal results but is assuming prior knowledge of the energy demand and when the vehicles are arriving and departing. The second contribution is to demonstrate that collaborative charging can be economically viable in the context of a strictly regulated market (such as Québec), achieving a win-win situation when shaving demand peaks of large electricity consumers while charging the cars for free.

The paper is organized as follows. The state of the art of V2B is detailed in Section 2. The system model along with explanations of the context where we are simulating collaborative charging are presented in Section 3. Section 4 presents the linear programming formulation for the optimization of the model. The methodology used in conducting the simulations is presented in Section 5, followed by simulation results and analysis in Section 6. Finally, we conclude our paper in Section 7.

2. State of the art

The concept of V2G has been exposed in preliminary works (Kempton et al., 2001) where it has been demonstrated as being technically feasible (Gage, 2003). Detailing the different possible usages of V2G (Tomić & Kempton, 2007) and financially assessing its capacity (Kempton & Tomić, 2004) was an important step in this research area. V2G concepts assume that electric powered vehicles will penetrate the personal transportation market en-masse and that this arrival could be a burden to the power grid (Ashtari, Bibeau, Shahidinejad, & Molinski, 2012). For instance, Shahidinejad, Filizadeh, and Bibeau (2012) used real-world vehicle usage data to predict the increased load on the grid associated with these vehicles using either a stochastic model or fuzzy-logic to decide whether or not the car should be plugged into a charging station between trips. The majority of studies agree on the necessity of aggregators to organize the future smart grid into multiple large entities, each one controlling a fleet of vehicles which independently do not represent a consequent power source (San Román, Momber, Abbad, & Miralles, 2011).

An important aspect of the aggregator is the actual decision making process in scheduling vehicle activity depending on the goal pursued. Sandels, Franke, Ingvar, Nordstrom, and Hamren (2010) proposed an aggregator model using Monte Carlo simulations applied to the German control market. Sekyung, Soohee, and Sezaki (2010) detailed the aggregator duties and used dynamic programming to maximize vehicle state of charge and participant revenues from frequency regulation. Binary particle swarm optimization has been used to maximize the vehicles owners' profits by selling excessive energy to the grid in a parking lot (Hutson, Venayagamoorthy, & Corzine, 2008), with expansion of this work to real time considerations (Venayagamoorthy, Mitra, Corzine, & Huston, 2009). Shi and Wong (2011) used the Q-Learning algorithm to control the real-time decision process on whether a vehicle should charge, discharge or provide frequency regulation under electricity price uncertainty. Managing a large number of vehicles (3000) was evaluated in Su and Chow (2012), using an estimation of distribution algorithm to optimize the charging schedule and maximize the average state of charge of the vehicles involved.

A linear programming model, also adapted to large vehicle fleets (10,000), was investigated in Sortomme and El-Sharkawi (2012), to take into account both bidding of energy and ancillary services. A stochastic dynamic programming model has also been proposed for the optimization of charging and frequency regulation capacity bids of EVs (Donadee & Ilić, 2014). Operation planning of a small electric energy system including renewable energy sources is described in Battistelli, Baringo, and Conejo (2012), using a linear programming model with few data at a time and taking into account uncertainties associated with charging/discharging patterns of EVs. Focusing on deployability, the comparison between a mixed integer linear programming model and its simulated annealing counterpart presented in Sousa, Morais, Vale, Faria, and Soares (2012) is positive for the latter both in terms of results and execution time.

García-Villalobos, Zamora, San Martí, Asensio, and Aperribay (2014) presents a survey of smart charging of EVs, identifying four main approaches: uncontrolled charging, off-peak charging, smart charging (valley filling), and smart charging (peak shaving). The last case corresponds to what we are looking for in the current work, by using the vehicles to manage the demand by charging the vehicles when the power demand is below the subscribed level (up regulation) and using energy available in the vehicles to shave peak demand (down regulation). This type of management of the power demand of a building is a form of demand-side management (Palensky & Dietrich, 2011) from the grid perspective.

In line with that, several studies have been conducted at the scale of buildings or microgrids. For instance, Pang, Dutta, and Kezunovic (2012) used EVs and plug-in hybrids in a V2B context for two distinct cases: demand-side management where only charging is considered, shifting charging from peak to mid-peak time, and outage management where the vehicles power the building. Momber et al. (2010) explored how EVs can integrate with a building's energy management system, proposing a model implemented in DER-CAM (Siddiqui et al., 2005), allowing an economic analysis of the approach. Another model was proposed by Cardoso et al. (2013), again optimized with DER-CAM, this time optimizing over a simulated model of a medium office building staged in San Francisco in 2020. Finally, Shaaban, Ismail, El-Saadany, and Zhuang (2014) proposed a two-stage optimization process, the first stage through charging only and then the second stage by allowing vehicle-to-vehicle exchanges when customers' needs are not satisfied. Their approach has been evaluated through simulations on a 38-bus system model involving a mix of residential, commercial, and industrial customers and EVs parking lots.

The originality of the current paper relatively to the previous work is to develop the idea of collaborative charging. We do so by applying V2B in the context of regulated markets, which are common for electric utility companies acting as a natural monopoly in a given region. In such a context, the pricing model, generally determined by a public utility commission, is often not directly related to the supply and demand. However, the pricing model generally includes, at least for commercial and industrial consumers, both an energy and a power component, providing an incentive to keep demand within the subscribed power. The penalty for exceeding the subscribed power might be significant, such that peak shaving can be highly desirable in order to reduce the electricity bill of the consumers. Through this perspective, we demonstrate that we can achieve a win-win situation for both the vehicles and the building, by optimizing the V2B-enabled charging schedule of a fleet of EVs on the campus of Université Laval through historical power demand data and a realistic model that includes the pricing scheme used for large electricity consumers in Québec. To the best of our knowledge, such a model has not been conceptualized and analyzed before.

3. System model

This study will highlight the benefits of V2B when vehicles are to be connected to a parking or building infrastructure constrained with a fixed subscribed power rating. The specific example of the authors' campus of Université Laval is used for the remainder of the paper. Hydro-Québec, the provincial electricity provider, has a specific billing scheme for large power business customers involving the following in two components:

- the maximum value of either (1) the subscribed power or (2) the maximum power peak in kW in the month;
- the total energy consumption in kWh during the month.

The power component is an important part of the bill, accounting for approximately 40% of the total cost. The specificity of this billing scheme being the energy sold at a cheap and fixed price, depending on the season: 2.97 ¢ per kWh in summer and 2.99 ¢ per kWh in winter for the year 2011, while households pay 5.39 ¢ per kWh at all times. The cost of power is calculated in several steps. First the power value to be billed is determined by retaining the highest value in kW between the maximum real power demand, 95% of the apparent power demand, and the subscribed power. The raw price of power is then calculated by multiplying this power value by 12.18 $/kW and multiplying it again by the number of hours in the month divided by the number of hours in 30 days. However, the final cost of the power component takes into account two additional factors: a credit for supply at medium or high voltage (0.915 $/kW) and an adjustment for transformation loss (0.1670 $/kW in summer, 0.16230 $/kW in winter). In winter, the client must have an accurate rough estimate of his maximum power peak because if the value is over 110% of the subscribed power, a 7.11 $ daily penalty is applied per excessive kW (limited to 21.33 $ per excess kW monthly), in addition to the regular power price. Therefore power peaks, even for a very short time, can be extremely costly.

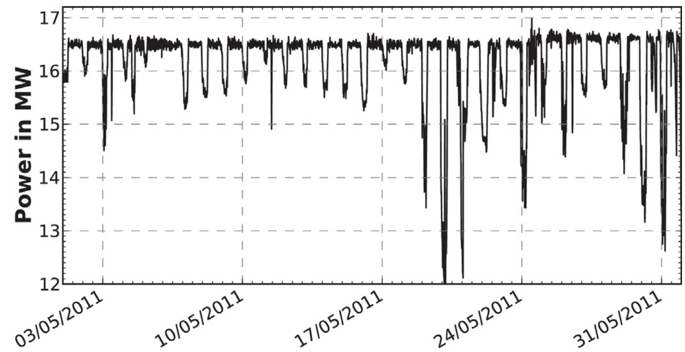

Fig. 1. Original real power consumption of Université Laval in May 2011.

Université Laval has an independent electricity network, and acquires its electrical energy via two 25 kV three phase power lines supplied by Hydro-Québec. Université Laval subscribes to a power of 15.75 MW and maintains its power factor between 0.95 and 1.0. This study uses real data provided by the Building Services of Université Laval campus. This data includes instantaneous power consumption for the whole campus every 15 min. Consequently each day is divided into 15-minute intervals for the simulation process, we make the assumption that the power drained by the campus remains stable during these intervals. This billing scheme was used in the model to determine the financial efficiency of V2B. Moreover, the campus uses an electric boiler to regulate its power consumption. For our study, we removed the power consumed by the boiler as this element is in direct competition with the use of V2B as it was specifically installed to take advantage of the tariff system through one-way regularization of demand. Fig. 1 shows the raw data available for the month of May 2011 before the electric boiler consumption component is removed.

The collaborative charging scenario investigated here aims at being beneficial for both parking lot users and the Université Laval in the following manner: with V2B the power component of the campus bill is reduced and the vehicles are allowed to charge for free in exchange for the right to control the vehicle energy.

4. Optimization

Linear programming is a mathematical method for convex optimization of a model expressed as a set of linear equations representing an objective function and constraints. Therefore, the objective function can be either minimized or maximized subject to linear equality and inequality constraints. The present work uses the revised simplex method and the primal-dual interior point method as implemented in the GNU Linear Programming Kit.[1] We choose linear programming as it is a gold standard in mathematical optimization and operation research, being a well-understood and robust approach to optimization.

The designed model aims at charging as many vehicles as possible while attempting to maintain the overall power consumption at or below a threshold which is the subscribed power. The model also considers the battery degradation induced by the V2B activity. The objective function to be maximized takes these concerns into account and should be read as the overall community benefits of

[1] Available at http://www.gnu.org/software/glpk/glpk.html.

V2B (all in \$), as given in (1):

$$\max \sum_{t=1}^{T}\sum_{i=1}^{N}\left[K_{chg}z_i^t e_i w_i \alpha_i^t - (K_{chg}+K_{wear}) z_i^t \frac{1}{e_i} w_i \beta_i^t\right] - K_{peak}\gamma^d - K_{penalty}\gamma^w, \quad (1)$$

with the sum computed over time steps $t = 1, \ldots, T$ and cars $i = 1, \ldots, N$. Greek letters denote the decision variables (explained next). The optimization is subject to several constraints:

$$0 \le \alpha_i^t \le 1, \quad \forall i, \quad \forall t, \quad (2)$$

$$0 \le \beta_i^t \le 1, \quad \forall i, \quad \forall t, \quad (3)$$

$$0.2\, C_i^{\max} \le C_i^0 + \sum_{j=1}^{t} c_i^j \le 0.8\, C_i^{\max}, \quad \forall i, \quad \forall t, \quad (4)$$

$$\gamma^d \ge 0, \quad (5)$$

$$R - P^t + \gamma^d \ge 0, \quad \forall t, \quad (6)$$

$$\gamma^w \ge 0, \quad (7)$$

$$R^w - P^t + \gamma^w \ge 0, \quad \forall t, \quad (8)$$

$$C_i^0 + \sum_{j=1}^{T} c_i^j \ge E_i, \quad \forall i. \quad (9)$$

The following parameters (constants) are given to the model:

- K_{chg}: charging cost per energy unit [\$/kWh];
- K_{wear}: cost of the battery wear-off induced by discharging a vehicle [\$/kWh];
- K_{peak}: cost of the power consumption exceeding the subscribed power value [\$/kW];
- $K_{penalty}$: cost of the power consumption exceeding 110% of the original subscribed power value during the winter [\$/kW];
- z_i^t: Boolean indicating whether the vehicle i is plugged-in (1) or unplugged (0) at time step t;
- e_i: charger efficiency for car i when charging or discharging ($0 \le e_i \le 1$);
- w_i: maximum theoretical energy flow (obtainable at the grid side of the charger) from or to the vehicle in kWh per 15-minute period ($w_i = 15U_iI_i/60$, with U_i and I_i being RMS grid voltage and nominal RMS line current, respectively);
- E_i: minimum battery capacity requested when vehicle i is unplugged.

And the variables being optimized (decision variables) are:

- α_i^t: percentage of the charger power allocated to charging the vehicle;
- β_i^t: percentage of the charger power allocated to discharging the vehicle;
- γ^d: maximum power consumption exceeding the subscribed power value taking V2B into account;
- γ^w: maximum power consumption exceeding 110% of the original subscribed power in winter.

The objective function (1) can be decomposed into four elements: (1) the value of energy charged in the vehicles ($\sum_t\sum_i K_{chg}z_i^t e_i w_i \alpha_i^t$), minus (2) the value of energy removed for the batteries for supporting the grid, including the corresponding wear-out cost ($\sum_t\sum_i (K_{chg}+K_{wear}) z_i^t \frac{1}{e_i} w_i \beta_i^t$), minus (3) the increase of peak power value in the day ($K_{peak}\gamma^d$), and minus (4) the penalty for exceeding 110% of the subscribed power during winter ($K_{penalty}\gamma^w$).

The constraints (2) and (3) ensure that each charger is restricted to operating within 0 and 100% of its maximum nominal power respectively while charging and discharging the vehicle, hence enforcing charger operational power capabilities. Note that although it is not explicit in the constraints, the optimization objective given in (1) ensures that for an optimal solution, at most one value between α_i^t and β_i^t is non-zero for a given car i and time t. The maximum power capability w_i is expressed in terms of the number of kWh absorbed or supplied at the output of the charger per 15-minute period. The 15-minute period is used here as it is also equal to the time step t used in the computation. It is assumed here that such a maximum value is specified at the grid side and is the same when charging or discharging. The effect of factor e_i (charger efficiency) will act to reduce the available energy flow at the battery when charging (e_i factor before α_i^t in (1)) and increase the energy flow value at the battery when discharging ($1/e_i$ factor before β_i^t in (1)). For example, a charger that accepts 3.6 kW (w_i = 0.9 kWh/15 min) from the grid will push 3.35 kW into the battery when charging. During the discharging period, the battery will deliver a maximum of 3.87 kW to the charger, which will then push a corresponding maximum value of 3.6 kW into the grid.

We must enforce the battery capacity limits, and in order to do this we define in (10) the energy exchange for vehicle i at time step t derived from the objective function:

$$c_i^t = z_i^t e_i w_i \alpha_i^t - z_i^t \frac{1}{e_i} w_i \beta_i^t. \quad (10)$$

We also define C_i^0 as the initial level of charge of vehicle i in kWh and $C_i^{\max}$ the total battery capacity of vehicle i in kWh. Therefore, the constraint enforcing energy bounds in $[0.2\, C_i^{\max}, 0.8\, C_i^{\max}]$ of the batteries is expressed as (4). This relies on the assumption that the charging and discharging functions are linear and that we can use 60% of the amplitude of charge of the batteries (20–80%). Operating below 20% would diminish battery life substantially, and so significantly increase wear-off. If one wanted to test our model with vehicles having a state-of-charge (SoC) less than 20%, this would require some preprocessing to immediately charge the vehicle to a secure SoC level of 20% before enabling optimization for smart bidirectional charging. Over 80%, charging is switched to a constant voltage mode, with current varying over time, resulting in an asymptotically low charging rate. This type of non-linear charging cannot be properly modeled by linear equations, as required by linear programming. Moreover, charging over 80% would then be very slow, resulting in negligible gains for the whole system. Managing vehicles charged over 80% using our approach can be handled with our method by overriding the real charge level, using 80% instead. This will result in a greater reserve below which discharging for powering the grid will not be done. For example, a vehicle charged at 90% when connecting to a station can pretend to have an 80% charge such that it would never be discharged below 30% to power the grid. However, this results in relying on an inaccurate charging model when operating over the 80% (true) charging level, when recharging the car after an episode of grid support.

If a V2B strategy is implemented on the campus in order to limit the peaks and save money on the power component of the bill, exceeding the subscribed power has a negative effect on the objective function. Therefore γ^d has to be positive or null as shown in (5) and proper determination of the variable is enforced by (6). In winter, an additional penalty is applied for exceeding 110% of the subscribed power, γ^w is positive or null as shown in (7) and its value determined using (8).

Variables used to model the power consumption are:

- R: the initial subscribed power;
- R^w: 110% of the initial subscribed power;

Table 1
Properties of the EVs used in the experiments.

Parameter	Prius	Volt	Leaf
Battery capacity (kWh)	4.4	16.5	24.0
Maximum charger intensity (Amps)	15 AC	16 AC	125 DC
Maximum charger voltage (V)	240 AC	240 AC	480 DC
Charger efficiency (%)	93	93	93

- A^t: instantaneous power consumption (grid side) at time step t without V2B;
- $P^t = \sum_i (z_i^t U_i I_i \alpha_i^t - z_i^t U_i I_i \beta_i^t) + A^t$: instantaneous power consumption (grid side) at time step t with V2B;
- U_i: RMS grid voltage of vehicle i;
- I_i: maximum RMS charger intensity of vehicle i on the AC side. An assumption is made that U_i and I_i are in phase.

Additionally, R and R^w values can be subjected to adjustments in the simulation process in order to cope with unachievable objectives. If the power demand exceeds the subscribed power in previous days, then the value of the maximum power peak replaces the value of R. Similarly for R^w, if the power demand exceeds 110% of the subscribed power, then the value of the third maximum peak encountered so far replaces it – remember that the winter penalty in the billing model considers the three largest peaks exceeding 110% of the subscribed power encountered during the month.

Finally, we wish to avoid the situation where participating vehicles exit the campus with their battery depleted, hence we force each vehicle to leave the campus with at least a capacity of E_i, which can be seen as the minimum capacity needed for a vehicle to travel back home. The constraint (9) ensures that this minimum capacity when unplugging is respected, with T being the time step at which the vehicle is unplugged.

5. Simulation methodology

The system is built around a scalable number of vehicles which all have their own properties as described in Table 1. These properties reflect the specifications of three vehicles available commercially: the Toyota plug-in Prius hybrid 2012 (referred to as “Prius” thereafter), the Chevrolet Volt 2012 (another plug-in hybrid), and the Nissan Leaf 2012, which is purely electric. This gives us both level 2 and level 3 chargers. For this study, the assumption is made that only one type of vehicle is allowed to plug-in: either all Prius or all Volts or all Leafs. Eventually, a more realistic study would include various fractions of each vehicle type, but this is left for further research. Using one vehicle type will be sufficient in the argumentation, from which the conclusions will be drawn.

The optimization process and subsequent simulation of the impact of the decision sequence on our data is run on every day of a given month so that we can produce a monthly bill similar to the one Hydro-Québec would produce with the power consumption profile modified. We determined that most of the days follow a similar pattern both in terms of hourly usage and maximum power peak, whereas a few days in a given month exhibit an unusually high power demand. This effectively means that while we could reduce the power consumption for each day individually, this is not a satisfactory option as we would then increase the battery wear-out for no real gain as the maximum peak for the month is retained for the bill calculation and not the maximum peak of each individual day. Simulations are repeated with multiple predetermined parameters in order to compare the outcomes of different possible scenarios:

- Different vehicle fleet sizes: from 100 vehicles to 400 by a step of 100 (4 sizes).

Table 2
Parameters for simulating arrivals and departures of the cars.

Parameter	Minimum	Maximum	% fleet present
Night time	0:00 am	7:30 am	0%
Arrival time	7:30 am	9:30 am	Stochastic
Day time	9:30 am	3:30 am	100%
Departure time	3:30 pm	5:30 pm	Stochastic
Evening time	5:30 pm	12:00 am	0%
Arrival SoC (%)	20	80	

Table 3
Parameters of the optimization model.

Parameter	Summer 2011	Winter 2011
K_{peak}	11.1033 $/kW	11.1027 $/kW
$K_{penalty}$	–	7.11 $/kW
K_{chg}	0.0242 $/kWh	0.024 $/kWh
K_{wear}	0.2 $/kWh	0.2 $/kWh

- Different vehicle types: for each scenario, it is assumed that the complete fleet is present on the campus every working day with a progressive arrival and a gradual departure, as described in Table 2.
- Different subscribed powers: 16 MW and 16.4 MW.

In addition to 30,000 full-time students, the campus employs around 9000 persons and has 40 parking lots with over 10,000 spaces. The vehicle fleets considered therefore account for 1–4% of the total maximum number of vehicles parked.

The simulations take place on a daily basis, for each working day. Arrival SoC value, arrival and departure time of each vehicle are randomly initialized in the ranges given in Table 2. The arrival and departure times are determined using a uniformly distributed random number in the ranges while the arrival state of charge is determined using a triangular distribution centered on 50%. This parameterization aims to reflect the employees’ habits, not the students’ habits which are expected to be more random. The minimum battery capacity when unplugging a vehicle, E_i, is determined as:

$$E_i = \max(C_i^0, \min(0.8\, C_i^{\max}, 1.1\, C_i^{\max} - C_i^0)). \tag{11}$$

The values generated for E_i therefore represent 30–80% SoC for each vehicle in order to prevent them from leaving with less energy than required to make their trip back home.

Additionally the model parameters explained in Section 3 are given in Table 3. K_{chg} is the typical price for a household in Québec for 1 kWh minus the price for the campus for 1 kWh. This represents the gain of charging on the campus compared to doing so at home for the users. K_{peak} is directly issued from the Hydro-Québec billing model, and is the raw price of power minus a credit for supply at medium or high voltage minus an adjustment for transformation loss. This value of K_{peak} is then weighted by the number of days in the month divided by 30. A realistic K_{wear} was determined using a battery cost of 240 $/kWh for standard Li-ion batteries and an expected useful life of 1500 cycles from 100% to 20% SoC. Other more optimistic values for K_{wear} have also been tested in the event that the battery price decreases or if their useful life increases significantly.

Once the daily simulation run for one setup is completed, a monthly bill is generated combining the new maximum peak component (kW) and the revised energy consumption value (kWh) for the campus. The value of the bill is then compared to the original one.

6. Results and discussion

Results have been generated with the model presented for the months of January, February, and May 2011. These correspond to typical months selected from the most recent year we had in the power consumption dataset provided by the Buildings Services. We selected these months after inspecting the data and before conducting the experiments. They represent typical months with interesting features, such as power peaks observed on February 16th and in the last week of May, and more constant power demand in January 2011. The other months of 2011 were less interesting, as the power demand patterns were redundant with the three months we selected.

Four values are of interest for each simulation setup:

- Maximum power: The largest power peak in the month obtained with the V2B fleet considered. This value is used to calculate the power component of the electricity bill;
- Δ cumulative energy: The increase in energy consumption on the campus throughout the month due to V2B compared to the case with no vehicle plugged-in;
- Δ bill campus ($): The variation of the campus bill (reduced if negative, increased if positive) compared to the case with no vehicle plugged-in. This result includes the campus savings associated with the peak reduction and the additional costs associated with the recharging of the vehicle fleet batteries;
- User benefits: The gain shared by all V2B vehicle owners; this value is calculated combining the value of exchanged energy and the battery wear-off. This value is underestimated because it uses the price of residential electricity as billed by Hydro-Québec for the first 30 kWh consumed (the so-called *heritage pool*), which increases after that level. This is especially the case in most households of Québec in winter.

For the three months selected, the results extracted from the optimization show a cost benefit for the use of V2B in peak shaving mode. The cost benefit will vary depending on the number of vehicles, the subscribed power, and the type of vehicle considered. Table 4 shows the results obtained with V2B given the different parameters fed to the system. The results will be discussed for each of the three months, with an analysis of the distinct behaviors observed in each of the three cases.

Table 4
Detailed results for January, February, and May 2011 (SP: subscribed power). Bold results correspond to the best option globally (user benefits – Δ bill campus) for a month, while italicized results correspond to the most interesting option for the campus (option with the highest savings on the bill campus).

Car type	#	Maximum power (MW)		Δ cumulative energy (kWh)		Δ bill campus ($)		User benefits ($)	
		SP = 16 MW	SP = 16.4 MW	SP = 16 MW	SP = 16.4 MW	SP = 16 MW	SP = 16.4 MW	SP = 16 MW	SP = 16.4 MW
January 2011 (Original values: consumption = 9,661,833 kWh; monthly bill = 545,486 $; power peak = 16.55 MW; SP = 15.75 MW)									
Prius	100	16.22	16.40	3395.35	3187.1	−4256.52	−1906.78	−132.49	166.4
	200	16.16	16.40	6742.06	6513.52	−4877.46	−1793.47	−138.84	356.35
	300	16.14	16.40	9865.27	9654.69	−5105.35	−1686.47	−67.39	535.72
	400	16.12	16.40	12,703.7	12,601.82	−5265.54	−1586.08	−7.14	704.0
Volt	100	16.17	16.40	11,861.08	11,921.72	−4614.99	−1609.25	167.2	665.17
	200	16.13	16.40	23,929.55	24,395.81	−4768.76	−1184.33	716.34	1377.46
	300	16.13	16.40	35,045.1	36,175.2	−4345.01	−783.09	1335.99	2050.09
	400	16.14	16.40	45,201.5	47,226.93	−3898.88	−406.62	1934.84	2681.17
Leaf	100	16.08	16.40	17,542.25	17,335.75	−5634.9	−1424.82	47.7	974.32
	200	16.03	16.40	34,764.64	35,479.87	*−5647.22*	−806.76	834.18	2010.38
	300	16.04	16.40	50,648.35	52,613.53	−4987.15	−223.11	1790.42	2988.75
	400	16.05	16.40	65,531.5	68,688.78	**−4364.87**	324.48	**2691.37**	3906.68
February 2011 (Original values: consumption = 9,064,530 kWh; monthly bill = 509,228 $; power peak = 16.98 MW; SP = 15.75 MW)									
Prius	100	16.66	16.66	3144.58	3088.26	−3615.11	−3617.03	−82.75	47.5
	200	16.60	16.60	6301.61	6249.02	−4278.63	−4280.42	−123.99	178.74
	300	16.56	16.56	9224.3	9208.82	−4638.08	−4638.61	−93.55	314.91
	400	16.53	16.53	11,991.84	11,965.81	−4877.81	−4878.7	−49.95	446.64
Volt	100	16.60	16.60	11,083.56	11,271.37	−4155.77	−4149.37	151.3	462.14
	200	16.57	16.57	22,395.45	22,907.48	−4019.38	−4001.94	680.11	1110.03
	300	16.58	16.58	32,810.74	33,883.81	−3612.97	−3576.42	1253.54	1740.58
	400	16.59	16.59	42,429.44	44,142.77	−3175.99	−3117.63	1824.39	2334.04
Leaf	100	16.48	16.48	16,677.41	16,440.37	−5278.62	*−5286.7*	−44.01	650.3
	200	16.48	16.48	33,320.51	33,380.98	−4746.15	−4744.09	785.96	1614.21
	300	16.48	16.48	47,703.16	49,290.7	−4236.43	−4182.35	1625.48	2524.66
	400	16.50	16.50	60,721.18	64,209.15	−3628.31	**−3509.5**	2470.0	**3392.93**
May 2011 (Original values: consumption = 9,239,864 kWh; monthly bill = 534,464 $; power peak = 16.97 MW; SP = 15.75 MW)									
Prius	100	16.61	16.61	3358.97	3358.97	−4591.94	−4591.94	146.65	146.65
	200	16.39	16.40	6888.42	6929.42	−7350.86	−7226.4	212.68	225.63
	300	16.35	16.40	10,167.34	10,221.65	−7808.13	−7115.01	343.38	413.62
	400	16.32	16.40	13,206.48	13,309.12	−8011.46	−7010.54	487.9	589.92
Volt	100	16.59	16.59	12,515.15	12,515.15	−4595.84	−4595.84	661.42	661.42
	200	16.37	16.40	25,237.43	25,444.93	−7032.77	−6599.92	1232.22	1282.9
	300	16.37	16.40	37,333.54	37,533.33	−6551.93	−6190.9	1929.67	1973.17
	400	16.38	16.40	48,643.0	48,784.21	−6056.99	−5810.22	2586.05	2615.62
Leaf	100	16.28	16.40	18,193.94	18,268.47	*−8409.34*	−6842.74	704.05	873.11
	200	16.24	16.40	36,805.59	37,276.6	−8260.95	−6199.58	1700.04	1958.51
	300	16.25	16.40	54,403.73	55,226.15	−7563.69	−5592.24	2719.93	2983.47
	400	16.26	16.40	70,874.48	72,066.88	**−6952.3**	−5022.4	**3667.86**	3945.11

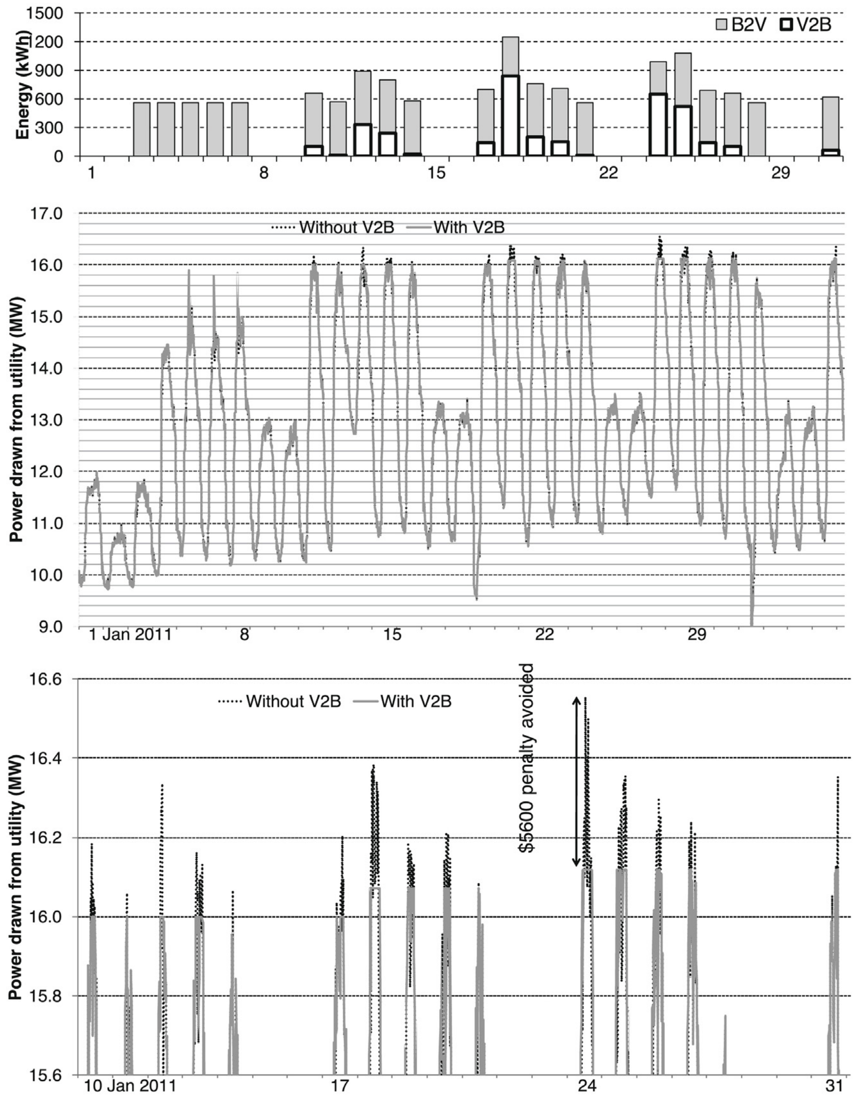

Fig. 2. Power consumption and energy exchanges for the month of January 2011 with 400 Prius and a 16 MW subscribed power. The top figure shows the energy exchanges between the car and the building; the middle figure presents the power calls over the month with and without V2B; and the bottom figure is an excerpt of the power calls figure with the highest peak over the month. Note that in the top figure, the bars are overlapping, both bars starting at zero, the differences between them corresponding to the net energy given to the vehicles.

For January 2011, the original cost of electricity for the campus was 545,486.10 $, the original maximum power peak was 16.55 MW, and the total consumed energy accounted for 9,661,833.68 kWh. Interestingly, the system optimization leads to advantageous benefits when providing peak compensation in association with an increase in the campus subscribed power. Leaving the subscribed power at 15.75 MW would produce a financial burden in terms of battery wear-off that is not sustainable for the users. The results indicate that a slight increase in the university subscribed power in combination with peaks shaving is a better choice, as presented in Table 4 for a subscribed power increase to either 16 MW or 16.4 MW.

Prius in January 2011. In January 2011, aiming for a 16 MW subscribed power does not produce satisfactory results for Prius vehicle owners, due to the size of their battery pack. The battery wear-off associated with the massive discharge of the vehicles is not financially compensated for by charging them. Indeed, the energy storage capability available to the system is not large enough to make it financially appealing for the community. An example of this behavior is shown with a fleet of 400 Prius in Fig. 2, which indicates that energy flows in both directions 15 days out of 31 days of January 2011. Although less beneficial for the drivers, the Prius has a strong effect in reducing the campus bill due to the small battery size and, therefore, low energy consumption for a 20–80% recharge, while still providing a peak demand shaving capability comparable to the Volt.

Leaf in January 2011. However, as the fleet size is increased for both Volt and Leaf fleets, users gain more from participating, the energy storage constraint being lifted. With 16 MW subscribed power, a 200 Volt or Leaf fleet yields the best financial advantages for the campus. Larger fleets of these vehicles will slightly increase the campus bill, while significantly increasing the user benefits, a 400 Leaf fleet providing the best global option for both users and the campus. As a matter of fact, when the fleet size increases, the number of kWh supplied by the campus to the vehicles also increases, thus increasing the campus bill.

Increasing the subscribed power with V2B. Interestingly, increasing the university subscribed power from 15.75 MW to 16.4 MW with V2B is still beneficial for the campus, with a more moderate use of the vehicle batteries and less wear-off. Nevertheless, the financial advantage is still greater with 16.0 MW compared to 16.4 MW due to the extra cost associated with the higher subscribed

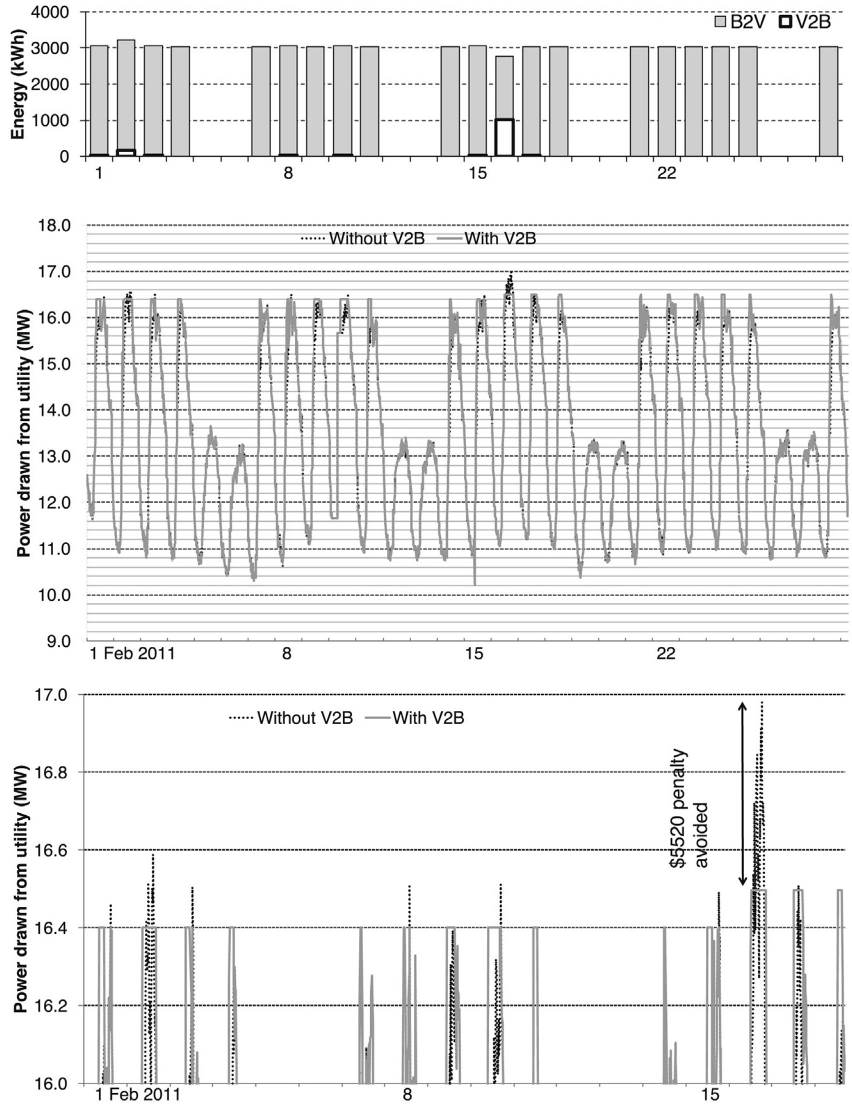

Fig. 3. Power consumption and energy exchanges for the month of February 2011 with 400 Leafs and a 16.4 MW subscribed power. The top figure shows the energy exchanges between the car and the building; the middle figure presents the power calls over the month with and without V2B; and the bottom figure is an excerpt of the power calls figure with the highest peak over the month.

power. The combination of a powerful charger and a large energy capacity in the fleet leads to an increased campus bill for 400 Leafs, given that the amount of energy required by the cars is the largest compared to the other tested configurations. It is interesting to note that the maximum power peak achieved with Volts and Leafs for a 16 MW goal first decreases with an increasing fleet size, given better capacity to manage the demand, and then increases again, as the larger battery storage requires more energy overall.

One day of excessive power demand in February 2011. The results for February exhibit more peaks, which are spread out throughout the month. The original cost of electricity for the campus is 509,228 $, with 9,064,529 kWh consumed and a maximum power peak of 16.98 MW. In the original campus bill, the maximum power call of 16.98 MW was prominent on the sole day of February 16, leading to a significant penalty due to over-consumption of 1230 kW of electrical power over the original 15.75 MW subscribed power. With such a high power peak, even a fleet of 400 Leafs cannot keep the system demand peak below the 16.4 MW subscribed power threshold. These results are a prime example of how determining the subscribed power value as accurately as possible is important for the implementation of such a system. In this particular example with a 16.4 MW subscribed power, the system is always beneficial for both the users and the campus. This contrasts with results obtained for January and 16 MW, where the power peaks are reduced and spread out over the month. Indeed, for February, V2B is easily able to shave a single high peak with a significant impact on the campus bill, while January requires that the campus be fed with 100s of kWh from the vehicles on several days, which has a cost in terms of battery wear-out. The most interesting option for the campus is 100 Leafs, 16.4 MW. The best overall configuration for February is with a 16.4 MW subscribed power and 400 Leafs, the community gain rises to 6902.43 $ (i.e., user benefits – Δ bill campus, in this case 3509.50 $ + 3392.93 $). The representation of the power consumption and energy exchanges associated with this result is shown in Fig. 3. It is apparent from these results that the fleet contributes marginally throughout the month except on the 16th, when the strongest power peak occurs.

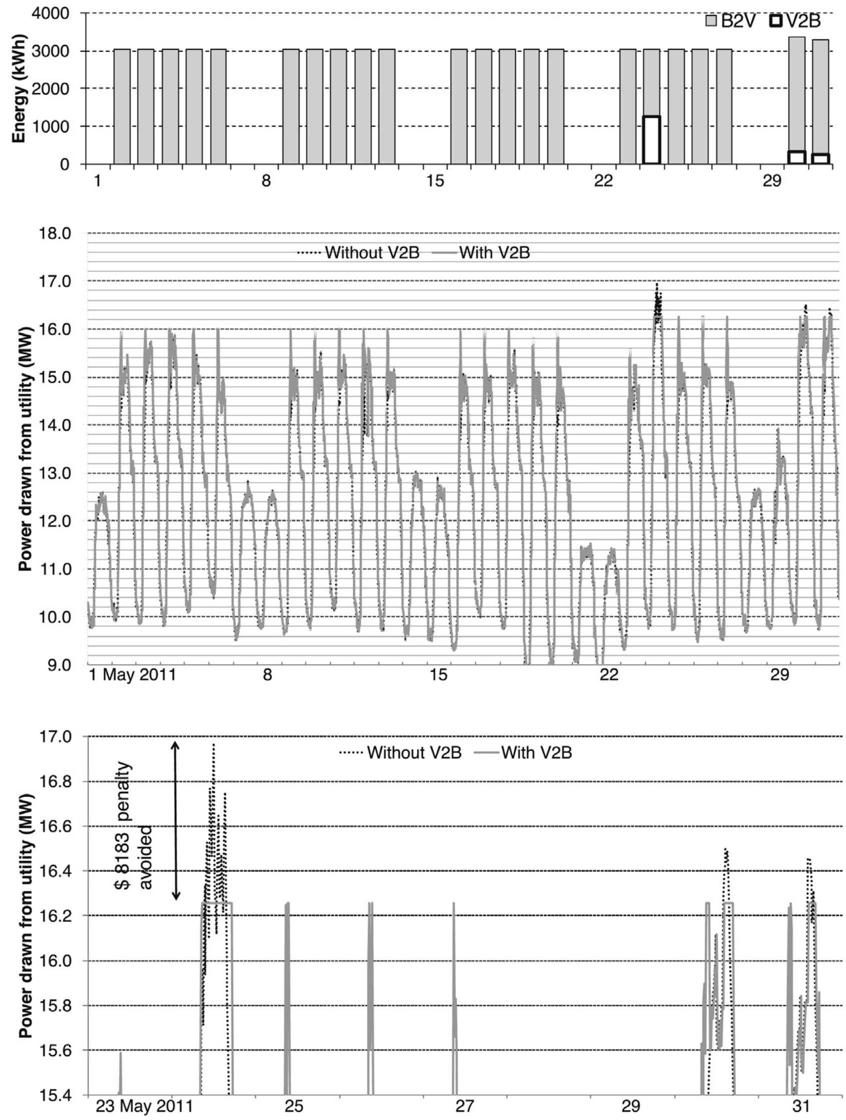

Fig. 4. Power consumption for the month of May 2011 with 400 Leafs and a 16 MW subscribed power. The top figure shows the energy exchanges between the car and the building; the middle figure presents the power calls over the month with and without V2B; and the bottom figure is an excerpt of the power calls figure with the highest peak over the month.

Adjustment of power demand threshold following peak days in May 2011. For May 2011, the original cost of electricity for the campus is 534,464 $, the original maximum power peak is 16.97 MW and the total consumed energy accounts for 9,239,864 kWh. The results for this month are the best yet encountered. Every configuration analyzed is beneficial for both the campus and the users even though the subscribed power is exceeded at 16 MW. The graphical results for a balanced case with 400 Leafs and a 16 MW subscribed power is shown in Fig. 4, since this represented the best option globally for both the users and the campus. Note that the most interesting option for the campus involves 100 Leafs, 16.4 MW. The results in Fig. 4 show that, once again, the fleet's major contribution in May 2011 is concentrated on a few days, here the 24th, 30th, and 31st which were in fact the hottest days of the month. The rest of the time, vehicles are simply recharged. The effect of the adaptive maximum power goal of the model is best seen in Fig. 4, the peaks never exceeded 16 MW before the 24th. On the 24th, the Leaf fleet could not provide the power needed on this day to remain below the 16 MW threshold. Yet, the power drawn from the utility could be reduced from a previous maximum of 16.97 MW down to 16.26 MW. After the 24th, a new increased threshold of 16.26 MW is used for the remainder of the month, as the 260 kW power penalty will be billed in any case. This month also exhibits the greatest power peak reduction with 710 kW fed to the campus by the vehicles.

The possible viability of collaborative charging has been demonstrated, with values that are realistic and a technology that is currently available. However, the future might provide even brighter results, which represents a strong incentive to invest in this research area and, deploy systems on a large scale. Table 5 presents what would happen to the user benefits should a leap forward be made in the battery area. By lowering the K_{wear} value, we can turn an unwanted configuration into a profitable one, as is the case with a fleet of 100 Leafs and all Prius fleet sizes for 16 MW subscribed power.

Table 5
Results for different values of K_{wear} for February 2011.

	#	User benefits ($)			
		K_{wear} = 0.075		K_{wear} = 0.0375	
		SP = 16 MW	SP = 16.4 MW	SP = 16 MW	SP = 16.4 MW
Prius	100	74.67	124.82	121.89	148.02
	200	166.36	285.61	253.46	317.68
	300	278.68	441.49	390.35	479.47
	400	-390.96	588.65	523.23	631.25
Volt	100	440.31	571.05	527.01	603.72
	200	1039.4	1228.87	1147.19	1264.52
	300	1625.62	1857.15	1737.24	1892.13
	400	2183.51	2446.02	2291.24	2479.62
Leaf	100	553.89	823.42	733.26	875.35
	200	1456.11	1789.39	1657.15	1841.94
	300	2284.68	2698.65	2482.44	2750.85
	400	3068.49	3557.09	3248.04	3606.33

7. Conclusion

Using real-world data and realistic randomly generated behavioral patterns, this article demonstrates the financial viability of collaborative charging for both the “Building” and the vehicle owners in a regulated electric market such as the one in Québec, if the subscribed power and the fleet size are properly matched. The model presented here, with between 1% and 4% of all vehicles parked at the campus being plug-in hybrids or EVs, allow these vehicle batteries to be replenished to 80% of their capacity for free, while reducing the campus electricity bill by 0.9% and 1.6% compared to the no-V2B original scenario. In the study, the cost of battery wear-out has been considered, which may lead to high costs of battery degradation if the subscribed power is set too low. The determination of the subscribed power has proven to be a key parameter for a cost-efficient V2B peak shaving mechanism.

The advantage of such a system for the electricity supplier is not taken into account in this study. It would not be surprising that being able to more accurately predict power demand and reduce power peaks significantly, if such a system was generalized, would be of great interest to the utility company.

An important limitation of the current studies is that the real campus power demand and car parking schedule for each day are directly used by the optimization method. In practice, it is obviously not possible to obtain this information in advance, so the results reported in the paper should be considered as the upper bound of what can be achieved through collaborative charging in the tested setting. We plan to conduct further experiments by feeding the optimization process with forecasts of the power demand and car parking schedule, and then evaluate the extend performances with the real power demand and car availability data. An alternative would be to make use of online methods from reinforcement learning (Sutton & Barto, 1998), to replace linear programming, to produce the charging schedule. These methods would not require a prior knowledge of the power demand and car parking schedules. By comparing results obtained with these approaches to the results reported in the current paper, it would be possible to evaluate the extend to which these methods – which can be implemented in practice – would differ from the optimal results reported in the current paper.

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