An Explicit Battery Discharging Model to Enable Vehicle to Grid Services

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Abstract. With the increased use of electric vehicles, the discharge of electric vehicle (EV) batteries (vehicle to grid, V2G) has been repeatedly proposed as enabler of smart grid services. In this work we describe the weaknesses of current discharging models and propose a model based on explicit discharging tasks. Using simulation in a microgrid control architecture, we realize several V2G use cases that involve aggregated loads and EVs, obtaining promising results.

Keywords: V2G · EV discharging model · Energy flexibility · Charging station · Demand management · Charging optimization · MPC · Microgrid · Mathematical programming

1 Introduction

Following the seminal papers of Kempton and Tomic [1,2] in which the authors present scenarios and business cases for supplying energy to the grid from batteries of plugged-in electric vehicles (PEV), a large number of publications emerged to analyze the benefits and drawbacks of the vehicle to grid (V2G) technology. At the time of writing the trend to efficient and "clean" EVs is unbroken, and the fact that private owned EV remain parked 90% of the time makes the use of the car battery for buffering energy appealing.

One of the most viable scenarios for V2G used in the integration of renewables into the grid to meet peak load by storing the energy from solar peak to the load peak, see [1,12]. Since the renewable power generation rate fluctuates strongly, the power output is often curtailed to reduce the variation. G2V and V2G would help to absorb these variations without curtailing.

In [3] the authors review the revenue opportunities of different use cases for the energy stored in EV batteries: regulation (frequency control), reserve (e.g. spinning capacity kept aside for cases of sudden power loss), renewable energy exploitation. The authors however warn that saturation in the reserve market would probably reduce the attractivity of such services. Although the revenues from V2G can attain several hundred dollars per year and vehicle, the authors of [3,4] arrive to the conclusion that most benefits of V2G can be provided as well through unidirectional, controlled charging.

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Several works [5,6,11] assume that the battery of an EV can be discharged anytime (if the EV is plugged-in) similarly to a fixed battery. We argue that this mode of operation has serious drawbacks, especially when a fleet of EVs is to be controlled, as we will point out in Sect. 2.

The prevalent model of anytime discharge of a plugged-in EV battery has a main drawback, as the EV owner has no control over the frequency and intensity of charge/discharge operations, as we will explain in the next section.

Therefore, similarly to charging tasks, we propose the introduction of explicit discharging tasks, as elements of future V2G services. These tasks are characterized by start and end times, by the amount of energy to be discharged, or a minimum discharging power required by some services. The user maintains in this way the control over the battery degradation, understands the value of the energy (and of the service) as well as the state of the battery before and after the discharge. Based on this model, a number of V2G use cases are simulated and discussed.

The rest of the paper is as organized as follows: in Sect. 2 we describe the model for explicit discharging tasks, and derive the energy flexibility of EV battery charging and discharging. Section 3 describes the control architecture in which we embed the charging and V2G operations and formulate the optimization problem for a charging station. Section 4 provides simulation results and Sect. 5 summarizes the lessons learned.

2 Flexibility Models for EV Charging and Discharging

2.1 Anytime Discharge

Most of the previous works on bidirectional charging use a model similar to a fixed battery. Mostly controlled in real-time by voltage or energy price, these home batteries may still have a schedule, stating for instance that at a certain time of the day, the state of charge should not fall below a certain value. In general, any trajectory that reaches this value, via charging and discharging is feasible.

EV battery models require more constraints, first of all because of their availability periods. The primary objective is to charge the battery to a certain state of charge, until a given time. Controlled charging allows to achieve this goal via many trajectories and avoids overloading the local grid connection. However if we add the possibility of discharging, the process becomes uncontrollable, especially if the control applies to a whole EV fleet. Therefore, in order to implement energy management functions with V2G, some authors [5,6] use heuristics. It cannot be avoided however, that some of the vehicles have to charge in order to achieve the SoC in time, while other vehicles discharge to provide V2G power. This can be seen as a net transfer of energy from one battery to another and is an undesirable side effect.

Moreover, the number of discharges and their intensity cannot be controlled with this model, therefore the battery deterioration cannot be estimated nor limited and compensation for this degradation cannot be calculated in the business model.

2.2 Explicit Modelling of Charging and Discharging Tasks

The proposed model is applicable to single PEV, a charging fleet or to a general EV service operator.

The mobility pattern has a considerable impact on the effectiveness of V2G operations; for example, in a working and living neighborhood, a part of the vehicles leave in the morning and arrive in the afternoon, while another part arrive in the morning and leave in the afternoon. Without explicit discharge tasks, V2G operations are not possible neither in the morning (because the just arrived cars have to charge first), nor in the afternoon, etc.

Crucial for the charging and discharging operations are energy and power flexibility. In Fig. 1 we illustrate the energy flexibility of a charging task, before the car is available at $t^a = 1$. Charging can be performed with power $p \in [0, p^c_{max}]$, $p^c_{max} = 2\,\text{kW}$, but in order to reach $E^c_{min} = 4\,\text{kWh}$ by the time $t^d = 6$, the car has to start charging at t = 4 at the latest.

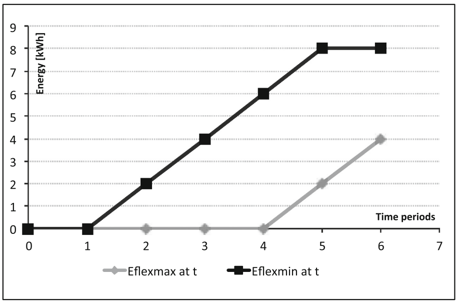

Fig. 1. Energy flexibility of a EV charging task

The first model we introduce is the **Energy based discharge task**. For the qualitative discussion we assume that the EV availability forecast is perfect, and neglect the energy losses of approximatively 12% [12] in charging and discharging.

The proposed discharge model defines a discharge task in a time interval $[t_a, t_d]$, similarly to the charging task. The flexibility of a discharge task as it appears at $t = 0$ is illustrated in Fig. 2 for a vehicle available between $t^a = 1$ and $t^d = 5$. In general the minimum and the maximum amount of energy provided by the battery can be specified. The discharge power is $p \in [0, p^d_{max}]$ with $p^d_{max} = 3\,\text{kW}$. The amount of energy to be injected in the grid during $[t_a, t_d]$ is at least E^d_{min} and is given. How long in advance this information is known to the system and how it is negotiated between EV owner and aggregator, is a matter of the service design and will not be detailed here. In case of peak load leveling or ancillary services (see [3] for an overview of services) the aggregator could for example perform a request for bids.

Table 1. Notation summary

Notation	Description
$j \in N$	Index the time periods
$i \in M$	Index of charging or discharging task
t_i^a, t_i^d	Time interval for task i
p_j^{in}	Injected power from the grid at time j
p_{max}^c	Max. charging power
p_{min}^d	Min. discharging power
p_{max}^d	Max. discharging power
$\underline{P}_{ij}, \overline{P}_{ij}$	Power flexibility
$\underline{E}_{ij}, \overline{E}_{ij}$	Power flexibility
$e_{i,j}$	Energy charged until j
p_{ij}	Power charged/discharged during interval j
SoC^i	State of charge
E_{min}^c, E_{max}^c	Charging minimum demand
E_{min}^d	Discharging guaranteed demand

On a household level, a service would consist of buffering the generated renewable energy in the EV battery and then provide it to the household via discharging tasks that the user can configure himself.

Like any technology that was originally intended for another purpose (charging energy for driving), the approach used for discharging has also drawbacks: it requires the stakeholders to plan in advance, which implies that services with fast response such as grid frequency control or spinning reserve are probably difficult to realize. This applies in general to any stand-by service, as well as to outage or islanding scenarios.

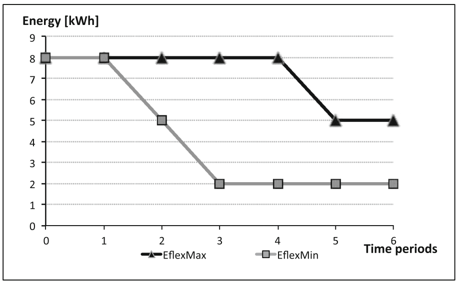

Fig. 2. Energy based EV discharge task

In a variant of the discharge task, the **Guaranteed power discharge task**, a minimum discharge rate p_{min}^d is specified in addition to the minimum energy amount, the maximum discharge rate and time interval. In Fig. 3 the discharge power can be selected between p^d_{min} and p^d_{max}. Any trajectory between the two curves, from the initial state of charge to the final SoC represent the same amount of energy discharged, in our example 28 kWh. The tangent at any point of the trajectory (the charging rate) must however be larger than p^d_{min}. Such a model might be required if a certain minimum power intensity has to be provided as part of the V2G service definition.

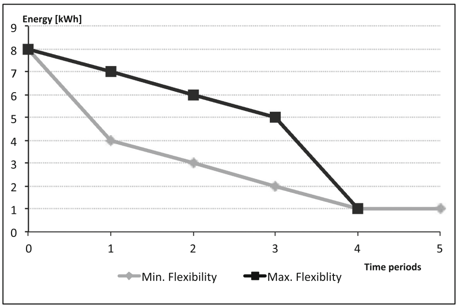

Fig. 3. Guaranteed power EV discharge task

3 Scheduling of Discharge Tasks in a Charging Station

We define a charging station as a parking lot and a fleet of PEVs, each connected to a charging point, so that controlled charging and discharging are possible. The charging station controller has the objective to optimize charging and discharging, such that the total load of the charging station follows the setpoints p^{ref} issued by a central controller (acording to a microgrid control architecture, for details see [7]). A factor that depends on the energy price c_j might be added to the objective. α is the weighting coefficient between the objective components. The local optimization problem at the charging station controller should satisfy the constraints (3), (4), (5), (6). For the schedule calculation, we use a simple model predictive control (MPC) [10] scheme in which the variables p, p^{in}, e, etc. are computed for the future N timeslots in each control loop iteration. It has to be noted that any other model that exploits the flexibility information from the charging and discharging models could be used instead.

$$min : \sum_{j \in N} (\alpha(p^{in}_j - p^{ref}_j)^2 + (1-\alpha)c_j p^{in}_j) \tag{1}$$

$$p^{in}_j = \sum_i p_{ij} \tag{2}$$

$$\underline{P}_{ij} \leq p_{ij} \leq \overline{P}_{ij}, t_i^a \leq j \leq t_i^d \tag{3}$$

$$\underline{E}_{ij} \leq e_{ij} \leq \overline{E}_{ij}, t_i^a \leq j \leq t_i^d \tag{4}$$

$$e_{i,j} = 1/T p_{i,j-1} + e_{i,j-1} \tag{5}$$

$$e_{i,0} = SoC_i \tag{6}$$

$$\underline{E}_j^{CS} = \sum_i \underline{E}_{ij}; \underline{P}_j^{CS} = \sum_i \underline{P}_{ij} \tag{7}$$

$$\overline{E}_j^{CS} = \sum_i \overline{E}_{ij}; \overline{P}_j^{CS} = \sum_i \overline{P}_{ij} \tag{8}$$

3.1 Aggregation Optimization Model

At the top of the control scheme we use an low voltage grid (or microgrid) aggregation controller that supervises a set R of nodes composed representing residential loads, commercial loads and charging stations.

The limiting constraint in the aggregation function model is the rated power at the transformer (similar to the problem definition in [6]). Using the same model predictive control scheme, the aggregator solves the optimization problem (9, 10, 11) below, in each of the timeslots of the time horizon T, and calculates the setpoints for all the nodes in the microgrid, including the charging station. A setpoint for node i is related to its power consumption prediction by the relation: $p_i^{ref} = p_i^{in} + \beta_i.\ p^{in}$ and the flexibility information can be provided by the nodes using a Demand Response communication protocol, such as OpenADR. The model uses the values of $\underline{P}^{CS}$, $\overline{P}^{CS}$, the predicted power consumption P^{in}. In the objective (9), we want to minimize the difference between the setpoint at time t and the setpoint at time t-1, similarly to [9], therefore we denote $p_i^{ref-} = (p_i^{in} + \beta_i)|_{t-1}$

minimize

$$\alpha \sum_{i \in R} \beta_i^2 + (1-\alpha) \sum_{i \in R} (p_i^{ref} - p_i^{ref-})^2; \alpha \in [0,1] \tag{9}$$

subject to:

$$\sum_{i \in R} (p_i^{in} + \beta_i) \leq P^{LV} \tag{10}$$

$$\underline{P}_i \leq p_i^{in} + \beta_i \leq \overline{P}_i, i \in R \tag{11}$$

4 Simulation Experiments

In the simulation experiments below we use a microgrid control architecture [7]: each charging station and each building has associated an energy management controller (CEMS); these controllers report to an aggregation controller that computes the appropriate setpoints for each facility.

Table 2. Parameters of the EV charging and discharging tasks used in the simulation experiments

Charge task	p^c_{max}	Charge t^a_i	dur[h]	E^c_{min}	Discharge task	Discharge t^a_i	dur[h]	E^d_{min}
C01	11	06:00	6	6	D01	15:00	4	-6
C02	12	07:00	9	8	D02	16:00	5	-8
C03	11	08:00	9	10	D03	17:00	4	-10
C04	12	10:00	2	4	D04	15:00	5	-6
C05	11	09:00	8	6	D05	16:00	4	-8
C06	11	14:00	2	5	D06	15:00	4	-5
C07	11	12:00	2	4	D07	16:00	5	-4
C08	11	07:00	9	8	D08	16:00	4	-8
C09	9	08:00	9	9	D09	16:00	4	-9
C10	12	09:00	8	7	D10	16:00	4	-7
C11	12	06:00	3	6	D11	16:00	4	-6
C12	11	08:00	3	6	D12	16:00	4	-6

In a first set of experiments we show that the load of a charging station can be strongly reduced if needed, thanks to the builtin flexibility. For this purpose, we artificially limit the total load and measure the charging performance of individual charging tasks. The simulation setting consists of 12 EV charging tasks associated to a charging station (see Table 2). The load limit P^{LV} is set to 8, 10 and 15 kW. Figure 4 shows the total charging load. In the 8 kW case the setpoint is not followed exactly, however for all three runs the energy demand E^c_{min} is fully satisfied.

The second experiment illustrates the peak load shaving use case. The same charging station controller manages now 12 discharging tasks which have been planned for the afternoon (3 pm to 8 pm), see Table 2. We assume that the batteries have the necessary amount of energy, for instance because they have been charged previously from PV generated power. For the load we use the models developed in the IRENE project [7,8] in which different buildings with critical and flexible load are available. We have selected two apartment blocks with 24 apartments each, with PV generation and flexible consumption (air condition). The whole microgrid load is limited to 70 kW to simulate the peak shaving requirement. In Fig. 5 we depict the total load after using the V2G discharging tasks and achieve the peak load reduction. It can be seen that the aggregated discharge based on V2G works and reduces the peak that otherwise would reach

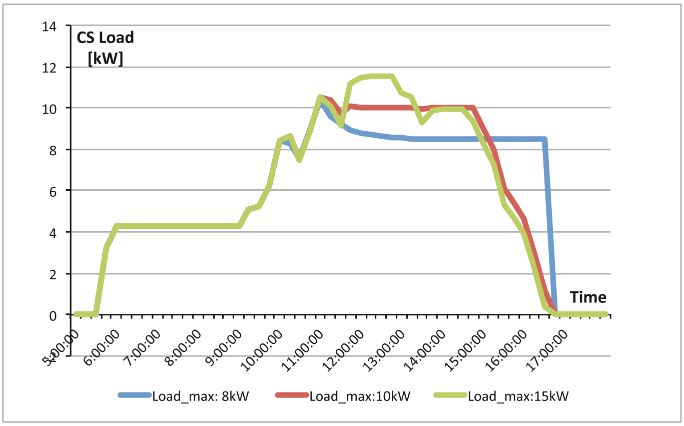

Fig. 4. Limiting the load of 12 charging EVs to 8, 10 and 15 kW

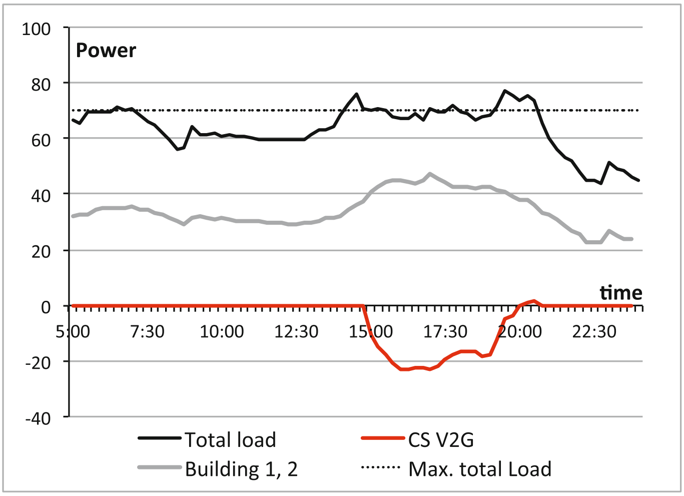

Fig. 5. (a) Charging station discharge only, (b) buildings load, (c) combined load

90 kW. We argue that such a behaviour cannot be achieved with the "anytime discharge" model presented in Sect. 2.1.

Finally, we adapt our simulation system to the use case of a single household that uses V2G for buffering renewable energy between the generation (midday) and consumption time (evening). Figure 6 shows only the discharging schedule: the discharge task is defined as follows: start at 6pm, duration 6 hours, $= E^d_{min} = E^d_{max} = -6$ kWh. If we require that the net power consumption of the house remains positive, then we obtain the behaviour in Fig. 6. The household power consumption is nicely mirrored by the discharge task, except for a few transient spikes.

Fig. 6. Renewable integration for single house using a discharge task

5 Discussion and Concluding Remarks

In this work we analyzed two different models for discharging vehicle batteries: the first one ressembles to a home battery model, where no constraints on the number or intensities of discharging operations are imposed, and the second one, described in detail, defines a discharge job with a defined amount of energy.

Using the first model in a peak load shaving scenario we observed that almost no discharging takes place. The are several reasons for that, one is that charging flexibility is normally sufficient to address peak shaving. This holds for the whole charging period, which in case of controlled charging spreads over the whole parking period. In addition, discharging is associated with costs (it degrades the battery life time), therefore it comes as last alternative in achieving the optimization objective [3].

Although many scenarios have been proposed for V2G, three most viable have been simulated using the discharging task model and the results are promising. The discharging tasks can be managed by the user, increasing the acceptance and offer a clear basis for compensation and for estimating the battery degradation.

For the realisation of V2G scenarios that are beneficial to aggregated loads, more research related to the realisation of business models and payment possibilities to compensate the EV owners of the V2G service is needed.

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