A Digital Twin for Coupling Mobility and Energy Optimization: The ReNuBiL Living Lab*

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Abstract. This paper presents a use case in the energy domain showing the benefits of digital twins. More specifically, we study the problem of peak shaving, which aims for managing a micro power grid in such a way that the energy demanded from the surrounding global power grid does not exceed certain limits. We examine a living lab consisting of university buildings as power consumers and power buffers in forms of fixed installed batteries as well as power-to-grid capable electrical vehicles that are booked by users. We provide a formal model of the relevant aspects of the micro grid and show how an artificial intelligence based prediction established from historical data as well as suitable simulation and optimization algorithms help to improve peak shaving.

Keywords: grid stabilization · bi-directional charging · car sharing

1 Introduction

The ongoing transition to renewable and climate-neutral energy sources, such as wind and solar power, means that the production of electrical energy becomes more volatile and fluctuating on a daily and seasonal scale. This creates a need for technical solutions to intermediately store electrical energy, and to better forecast energy supply, in order to meet the demand.

However, technical solutions on the energy supply side alone will not be sufficient; instead, more flexibility on the consumption side and user participation will also be necessary. For instance in Germany, the largest electricity market in Europe, the installation of smart meters in private households will soon become mandatory and allow more consumers to shift load to times when energy is more abundant. Particularly energy-intensive devices, such as heat pumps or wallboxes for electric car charging, get subsidized if they include communication links that allow grid providers to switch them off temporarily[1].

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[1] Energy Industry Act (EnWG), §14a Network-oriented control of controllable consumption devices and controllable network connections, German Federal Ministry for Economic Affairs and Climate Action (BMWK), 2022

Besides the energy sector, the mobility sector is still a large source of climate gas emissions. Battery-powered electric vehicles (BEV) have the potential to reduce carbon emissions, if operated with green electricity; the positive effects can be even greater in a car sharing context when vehicles are shared among several users and thus the initial cost and carbon "backpack" of battery production is faster amortized. In addition, during idle times when the BEVs are parked and connected to the grid, their batteries can be used as buffers to store excess electricity and feed it back to the grid during peak demand times. Such so-called vehicle-to-grid concepts are now extensively studied in pilot projects [4, 6, 5] and corresponding norms for introducing bi-directional charging in the market have recently been rolled out [2].

In this paper, we study a use case, on the campus of our university, that combines both the mobility and energy domain. The scenario consists of a fleet of electric vehicles with bi-directional charging capabilities and a stationary buffer battery, connected to a micro grid with additional consumers (university buildings). The cars can be booked by car sharing users for trips, and the charging and discharging of the batteries (cars and stationary buffer) needs to be managed in such a way that the range of the cars remains sufficient for the trips, while the total power demand of the micro grid should never exceed a given limit (peak shaving). Peak shaving is important for grid stability, but also for electricity costs: grid usage fees, which make up a large proportion of the electricity costs, are based on the maximal power used in the billing period (monthly or annually), even if this maximum is reached only for a short period of time[2].

It is easy in this scenario to devise a simple controller strategy that will, at each point in time, try to stay within the power limit by immediately reducing the charging power and – if this is not sufficient and there is energy left in the batteries – feeding back energy from the batteries into the grid. However, in our setting such a (myopic) controller might (depending on the additional load of other consumers in the micro grid) render user bookings infeasible by failing to charge the cars on time, or discharging them below the range required for upcoming bookings.

In the following, we present a formal model of this vehicle-to-grid problem and a digital twin [1] solution that uses AI-based load forecasting, simulation, and optimization to intelligently improve the balance between peak shaving and user mobility. In particular, the approach will simulate the effect of requested bookings on the micro grid to recommend alternatives to users, while at the same time safeguarding already committed bookings such that the cars will have enough range for the desired trips. The system has been prototypically implemented and experiments have been conducted with carsharing users in a living lab on our university's campus.

The rest of the paper is organized as follows: Section 2 presents the case study and our living lab in more detail, and introduces a mathematical model to describe the problem formally. Section 3 describes our proposed digital twin so-

[2] This setting is typical for many energy providers, and e.g. also the case for the campus' energy provider.

lution based on forecasting, simulation, and optimization on this model. Section 4 concludes with a discussion and directions for further work.

2 Case study: The ReNuBiL living lab

In the EU-funded research project ReNuBiL[3] (living lab for user-oriented bi-directional charging), an infrastructure for experimenting with vehicle-to-grid concepts in the context of battery-powered electric vehicles shared among different users was set up on University of Lübeck's campus. It consists of (see also Figure 1):

- a Nissan LEAF passenger car with a battery capacity of 62kWh and approximate range of 385km
- a Nissan e-NV200 transporter with a battery capacity of 40kWh and approximate range of 275km
- two EVTEC[4] "coffee&charge" bi-directional charging stations with 20kW power output each
- an EVTEC "save&charge" stationary (second-life) battery with a capacity of 24kWh

The vehicles are connected to the stations using CHAdeMo plugs (direct current) for charging/discharging. The lab infrastructure is set up next to the largest lecture hall (Audimax) on the campus, and so the components are connected to the local micro-grid of this building that is part of the overall campus' power grid. Electricity meters were installed to record the energy flows (charging and discharging power, battery charge levels, etc.) in the lab and the adjacent Audimax building. Also, the vehicles themselves log data about their current position and energy consumption. The data is polled periodically and stored in a time-series database.

The vehicles can be booked by users via the project partner StattAuto[5], who operates a fleet of more than 200 cars in the region and has included the ReNuBiL vehicles in its carsharing system so they can be booked by any of their customers. The lab infrastructure (bi-directional charging stations and buffer battery) comes with an embedded software (EVTEC "barista") that controls the charging and discharging of the batteries (in the cars and the container) based on the overall grid load. More precisely, an upper limit (threshold) for the overall power consumption of the micro-grid (including the building and the lab components) can be set, and the controller software then tries not to exceed this limit, by appropriately reducing the charging power of the stations and – if this is not sufficient and there is energy left in the batteries – feeding back energy from the batteries into the grid. In this way, peak loads caused by the building's power consumption can be reduced, provided that the vehicles are idle

[3] http://www.renubil.de
[4] https://www.evtec.ch/
[5] https://www.stattauto-hl.de/

(i.e. not booked by customers for trips) and the charging levels of the batteries are sufficiently high.

StattAuto's current solution for safeguarding bookings is to leave a gap of three hours between bookings, enough for the vehicles to fully re-charge. Clearly, this is not optimal from the point of view of the carsharing operator but also in terms of peak shaving.

Fig. 1. ReNuBiL living lab on University of Lübeck's campus with two electric cars, two bi-directional charging stations, and stationary battery container

Problem Description. In our tackled setting, the cars are rented by customers and picked up at and brought back to the charging stations. While customers are free to charge the cars during a rental at third party stations, they are unlikely to do so except for very long trips. While it is technically possible to utilize the full charging power of the stations at all times, as outlined above our aim is to stay below a power consumption limit (in this setting of 45 kW) for the micro-grid including the charging stations, the stationary battery and the Audimax building.

Batteries can be charged from the grid while simultaneously other batteries are discharged into the grid. We therefore have a multilevel optimization problem: our highest priority is to enable bookings we have already confirmed to users. To this end, users have to provide their required range with each booking. Our second priority is to utilize both, the buffer as well as the car batteries in order to avoid exceeding the power consumption limit. Our third priority is to keep the cars available for short notice bookings, i.e. keep the cars charged as much as possible.

Parameters

$\text{bookings}_i \subseteq \{(t_1, t_2, r) \in R_0^+ \times R_0^+ \times R_0^+ \mid t_1 < t_2\}$
$\text{batCharge}_i : R_0^+ \to R$
$\text{batDischarge}_i : R_0^+ \to R$
$\text{efficiency}_i : R_0^+ \to [0, 1]$
$\text{demand}_i : R_0^+ \to R$
$c_i : R_0^+$

Variables

$\text{energy}_i : R_0^+ \to R_0^+$
$\text{power}_i : R_0^+ \to R$

Goal

$f : (R \to R) \to R$
$f(g) = \int_0^\infty \max(0, (g(t) - \text{limit}(t)))\, dt$
minimize: $f(\text{power})$

Constraints

(1) $\text{energy}(0)_i = c_i$
(2) $\forall (t_1, t_2, r) \in \text{bookings}_i : \text{energy}_i(t_2) = \text{energy}_i(t_1) + \text{demand}_i(r)$
(3) $\forall (t_1, t_2, r) \in \text{bookings}_i, t_1 < t < t_2 : \text{energy}_i(t) = 0$
(4) $\forall (t_1, t_2) \in \text{between}(\text{bookings}_i), t_1 < t \le t_2 : \text{energy}_i(t) = \text{energy}_i(t_1) + \int_{t_1}^{t} \text{efficiency}_i(\text{power}_i(t))\, \text{power}_i(t)\, dt$
(5) $\forall (t_1, t_2) \in \text{between}(\text{bookings}_i), t_1 < t \le t_2 : \text{batDischarge}_i(\text{energy}_i(t)) \le \text{power}_i(t) \le \text{batCharge}_i(\text{energy}_i(t))$
(6) $\forall (t_1, t_2, r) \in \text{bookings} : \text{charge}_i(t_1) >= \text{demand}(r)$
(7) $\text{power}(t) = \sum_i \text{power}_i(t)$

Fig. 2. Formal model of the peak-shaving problem for bi-directional charging and car-sharing

Formal Model. We first developed a formal model of our scenario depicted in Figure 2. The model describes the charging and discharging behaviours of the batteries involved. We treat both the car batteries as well as the immobile buffer battery the same as they differ only in their ability to be booked by users. Parameters and variables are indexed by the battery id i. For each battery, the model has the following parameters: bookings_i is the set of associated bookings comprising a start (t_1) and end time (t_2) and a required driving distance r. batCharge_i and disCharge_i assign a maximal charging or discharging power respectively to each level of charge. These parameters allow us to model the power restrictions of the batteries. efficiency_i assigns a efficiency factor to a level of (dis-)charging power to model the power loss during (dis-)charging. demand_i maps driving distance to energy demand and c_i specifies the initial charge energy of the battery.

The variables of our models are two functions: the charge energy of a battery by time energy_i and the current (dis-)charge power of a battery by time power_i. The model only is defined in terms of the energy stored in the batteries not the actual charge as the energy stored by charge varies with voltage. Charging and discharging are distinguished by positive and negative power values.

The possible solutions for the power and energy functions are now defined by (1) the initial energy, (2) the consumption of required energy during bookings, (3) the inability to use car batteries during bookings, (4) the charging/discharging according to the assigned power with respective efficiency when batteries are available, (5) the power restrictions of the batteries and (6) the requirement to provide the required energy for bookings before they start.

Optimization goals can now be expressed as functions reducing the accumulative power function power defined by (7). The optimization goal to minimize the excess of a power limit can be expressed by the function f defined in Fig. 2. The limit there depends on time and therefor can take the external power consumption into account.

Charge Strategy. During operation of the charging station the (dis-)charging of the batteries has to be constantly optimized according to the charging model and our optimization goals. Solving the constraint model on the fly can be difficult to impossible especially considering the non-linear behavior of battery constraints. We therefore designed a dedicated charge strategy that achieves our goals comprising the following rules:

1. for each battery, if we need to start charging at full power in order to facilitate the next (or a subsequent) booking, do so.
2. for each battery that remains, charge if we are below the limit, discharge, if we are above the limit.
3. prefer car batteries when charging, prefer buffer battery when discharging.

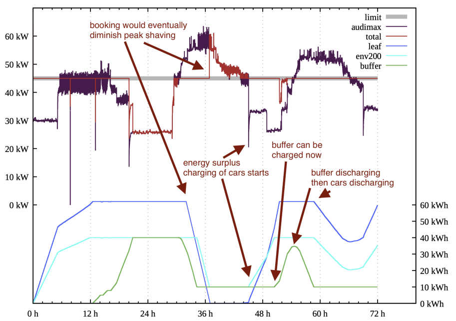
As our optimization goal is linear, i.e. exceeding the limit moderately for a long time is not better than exceeding the limit excessively for a short time, rules 1. and 2. result in an optimal strategy. Rule 3 deviates from that slightly to also optimize for availability for short notice bookings.

Booking Assessment. In contrast to other work [3], we are not considering a scheduling problem here: bookings are not scheduled but have to be assessed and facilitated when they are requested by the users. When a user wants to book a car, we provide him with a rating of that booking based on the optimization goal. This rating is computed by simulating the current bookings excluding and including the new booking according to the constraint model and the charge strategy. We then take the difference between the values of the goal function, i.e. the additional violation of the peak shaving power limit caused by adding the new booking. For high ratings, i.e. bookings that would force us to violate the limit by a large amount, we ask the user to consider changing his booking to a different time slot. The simulation incorporates a prediction of the future external power consumption, which is either done directly on multiple historical data traces or on a prediction generated by machine learning from these traces.

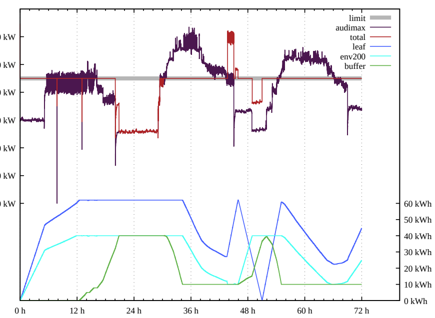
3 Proposed Solution: Digital Twin Approach

Our solution is based on the idea of a digital and a physical twin. The physical twin is constituted by the cars, the charging station and the university grid. The digital twin is constituted by the formal model of the charging station and car batteries, and the historical consumption data of the university grid and the machine learning model based on that data.

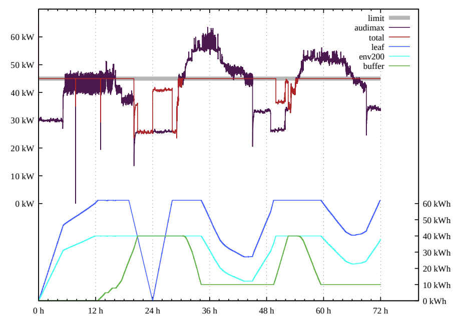
The physical charging station is controlled by the charging strategy designed above. The strategy provides control outputs to the battery control units and receives measurements from them as well as from the meters of the university grid. In addition, it receives minimal charge requirements for the car batteries that have to be observed in order to facilitate the currently confirmed bookings. These requirements are computed in the digital twin, i.e. the formal model using



(a) violation 33 kWh



(b) violation 21 kWh



(c) violation 0 kWh

Fig. 3. Simulated scenario

a backward simulation of the charging process with maximal possible charging power.

The second use case of the digital twin is the booking process: when requesting a booking, the user is provided with a rating. This rating is calculated by simulating the charging strategy over a prediction of the power consumption of the university grid. We support two prediction schemes: generating example traces from a machine learning model using LSTM neural networks according to [7] or directly using a set of historic traces. The rating presented to the user is then based on the average additional violation of the power consumption limit caused by the requested booking.

3.1 Simulation and Experiments

We have simulated our solution extensively using the setup described above. Let us explain our approach using a typical simulation for three consecutive days Sunday 00:00h to Tuesday 24:00h of a typical week during the lecture period (week 2 of 2023), as depicted in Fig. 3a.

Let us first concentrate on the upper part of the diagram. The purple curve shows the actual power consumption of the Audimax, our lecture hall acting as main consumer. We can see that the power demand is around 25-25 kW during night time and above 45 kW during day time with peaks up-to 70 kW on work days. This curve serves as a prediction of the Audimax power consumption for the simulated scenario.

The red curve shows the simulated total power consumption that would arise from running our charging strategy with one booking request for the Leaf with the given Audimax power consumption. The considered booking request starts at 32 h with a duration of 5 h and requires the complete battery capacity of 62 kWh.

The anticipated limit of energy consumption is set to 45 kW as depicted by the grey horizontal line. Whenever this limit is reached, the energy of the fixed installed batteries (buffer) and those of the electric vehicles may be used to reduce the energy consumption from the global grid. Whenever surplus power is available, the battery may be charged. We can observe this behavior starting from 45 h. The energy levels of the batteries are depicted in the lower part of the diagram, blue and cyan for the Leaf and the ENV200, respectively, and green for the buffer. As we can see, the system starts to charge the vehicle batteries as soon as surplus power is available. As there is not enough power available to charge the buffer as well and vehicles are prioritized, charging the buffer is delayed. Conversely, when the limit is reached at 54 h the buffer is discharged first.

Due to the booking, the leaf is not available from 32 h to 37 h and is completely discharged after the booking. As a consequence after 36 h the system is not able to maintain the power limit and the total power starts to coincide with the Audimax power consumption until 45 h. Note that the batteries have a discharge limit of 10 kWh. The system respects that limit but the vehicle batteries can be discharged further when driving.

In this scenario the limit would be violated by 33kWh which in this case is due to the single booking. Fig. 3b depicts how the scenario would change if we were to move the booking to 46 h. Here, we can observe how the system prioritizes bookings of the power limit. The system manages to uphold the limit up to 46h, but due to the booking then has to switch to charging the battery of the Leaf resulting in a large violation. Consequently, the violation in this sceario is still 21kWh.

Fig. 3c shows how moving the booking to 19 h, the previous evening, allows the vehicle to be charged over night, makes it available for power management during the day and allows to avoid the power limit completely. In total, we see that intelligent peak shaving works out in many situations yet going beyond the limit could not be completely avoided.

4 Discussion and Conclusion

Future energy systems will need a more tight and intelligent integration between different sectors, in particular the sectors of mobility and electrical power. This includes comprehensive sensor meter gathering, data-driven trend analysis and forecasting, and real-time mathematical optimization of control parameters. On the other hand, such systems must enable and support more flexibility on the user side, fostering the interaction with consumers to express their desires/needs and receive relevant information that allows them to adjust their behavior accordingly and contribute to overall stability and sustainability goals.

In this paper, we presented an approach towards this goal in the setting of electric car sharing and bi-directional charging. The batteries of the cars can feed back their energy into the local micro-grid, in order to limit the total power consumption of this micro-grid (which includes a building as further consumer). The users request to book the vehicles at certain times and for certain desired ranges, such that they are not available as buffers for peak shaving during these times and also need to be re-charged, creating further load on the micro-grid.

Our approach uses a digital twin model to balance the two conflicting concerns of limiting the grid's peak power and enabling user mobility. The digital twin allows to simulate and assess user's requests (at query time) and give recommendations to adapt their behavior (by shifting their bookings to earlier or later times of the day if possible). The user requests are typically issued several hours or days ahead of the actual bookings and so the evaluation/planning is based on predictions using historical data. In our setting, the objective to fulfill user's bookings is prioritized over the objective of peak shaving. Thus, during execution time, the digital twin model is used to appropriately switch between control strategies (fast charging to enable committed bookings, vs. peak shaving by reducing charging power and discharging energy from the batteries).

As another partner in the ReNuBiL project, the Institute for Engineering Psycholgy[6] studies possible incentives to motivate users to adjust bookings and participate in peak shaving. Clearly the system could also be further optimized if users could be aseked (and convinced) to re-schedule older, already committed bookings. Due to the involved user interaction via the car sharing provider, this case has not been considered so far.

Our current work includes the implementation of an alternative approach that uses constraint optimization on the formal model to synthesize optimal strategies, instead of selecting between pre-defined strategies (peak shaving and fast charging). However, while this would allow more flexibility and accuracy, the computational cost is much higher. Furthermore, we are trying to extend the machine learning approach to forecast not only the grid load, but also booking times. However, this turns out difficult as much fewer training data is available.

[6] https://www.imis.uni-luebeck.de/de

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