LOAD SCHEDULING AND V2G TO MINIMIZE POWER DEMAND – EXPLORING POTENTIAL FOR AIRPORT PARKING FACILITY, NORWAY.

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ABSTRACT

Electrification of transport introduces challenges but also opportunities. The challenges are increased power demand and possibly grid investment causing additional power demand cost for charging. However, electric vehicles are idle for long time periods, particularly at airport parking. This provides opportunities for scheduled charging in order to minimize power charges. We have developed an algorithm giving priority to charging the electric vehicle(s) closest to departure while minimizing monthly average power demand. We are applying the algorithm to data from a parking facility in the Oslo airport vicinity. We explore the potential for reaching the minimum average monthly power demand through scheduling and discuss briefly the cost and benefits of introducing V2G. The results indicate that all EVs may be charged with only a small increase in the monthly average power demand and V2G would not provide further benefits for the parking facility owner with the current power tariff in Norway.

INTRODUCTION

Electrification of transport introduces challenges for the electricity grid. The charging power of electric vehicles (EV) is high and uncontrolled charging can pose problems for the grid, especially the distribution grid, because charging typically increase peak load. Grøtan, Tveitane [1] observed two peaks in the number of charging sessions and thus peak power demand for charging at Oslo Airport Gardermoen (OSL), one in the morning and one in the afternoon. This is typically at the same time as residential and service peak power demand. High peak power demand increases the need for expansion of the electricity grid. Another option is to utilize the grid capacity better by reducing peak load, which in turn power tariffs could be an incentive for Norway, with a high share of electricity heating have high peak power charge during winter months [2]. Reducing peak power demand is thus attractive for the consumers and important for distribution system operator (DSO) to assure power security, the electricity grid's ability to meet the instant demand.

With smarter energy use, power demand and power costs can be reduced. V2G chargers currently have a high cost and thus require higher economic benefit. The optimal mix of one-way chargers and V2G chargers depends on the variation in electricity cost, power chargers, local demand for electricity, average parking time and difference in charger investment cost between one-way and V2G chargers. We explore criteria for combination of one-way- and V2G-chargers at the small parking facility Gardermoen Parkering (GP) located next to OSL, Norway. Particularly, we assess the impact of minimizing power demand cost.

The work presented here is part of the research project *Network balancing from large parking facilities and commercial buildings* (NeX2G), where we explore demand-side flexibility using electric vehicles (EVs) as energy storage, either with scheduled charging (load shifting) or vehicle-to-grid (V2G), in combination with flexible control of large assets in commercial buildings [3].

Case description

Gardermoen Parkering AS is a private owned parking lot situated directly outside of Oslo Airport Gardermoen in Norway. It offers inside and outside parking space for 1600 vehicles and has since 2009 had 90 chargers for EVs. In 2019, the electric consumption was 288 MWh. The peak power demand was around 60 kWh/h with the highest recorded power demand between 2019 – 2022 at 65,28 kWh/h. The load varies over time, and the consumption pattern for the parking lot has a strong S – shape in the load duration curve, see *Figure 1*.

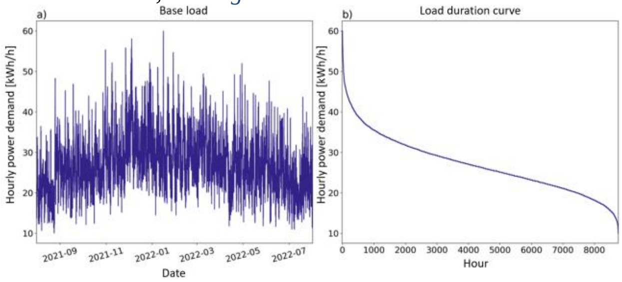

Figure 1 Electricity use at Gardermoen parkering in the vicinity of Oslo Airport, Norway, exhibit typical seasonal variation and diurnal peaks in power demand resulting in a strong S-shaped duration curve.

The energy consumption data for GP has hourly resolution and includes heating and other electricity consumption in the office building, and electricity consumption for the EV chargers.

Power charges in Norway constitute a significant part of the electricity cost. The power charge uses the highest hourly average power demand within a calendar month multiplied by a power tariff. The tariff varies depending on the power level category and may also vary between seasons and location, see *Figure 2*.

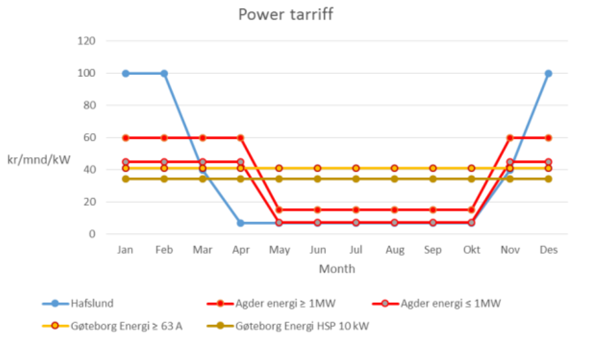

Figure 2 Power tariffs for the Oslo area (blue), a county on the Norwegian south coast (red) and city area of Gotenburg, Sweden

STRUCTURE AND OPERATION OF THE SIMULATION MODEL

The model objective is to find the minimum power demand required to meet the charging constraint. It applies a scheduling procedure where the EV(s) nearest to departure is charged first. The simulation model operates two steps calculating the hourly power demand, (1) without scheduled charging, and (2) with scheduled charging. In step 2 monthly average power demand is minimized. Initially we calculate the hourly energy demand for heating and service. The heating and service energy demand is equal in all scenarios. For each scenario power demand is calculated for step 1. Step 2 tests if all EVs may be fully charged within the average power demand. Subsequently, the power demand is increased by one percent until all EVs are fully charged upon departure. The variables defining the scenarios are number of chargers, number of vehicles requesting charging, charging power and state of charge (SoC) upon arrival.

METHOD

Data collection and preparation

The dataset from Gardermoen Parkering includes scheduled arrival and departure time for 55 282 vehicles parked in the time period from 09.17.2019 to 08.31.2022. Based on these data, a time series was generated. The number of vehicles parked at any hour in the time series is constant across the scenarios.

In Norway, only EVs have their license plate starting with E and are identified in the dataset. Together with assumptions about demand for charging, the electricity use for heating and service is estimated. Because of shorter time periods without data, the simulations only use data for the time period 01.05.2021 to 31.07.2022. This time period is also less affected by the covid 19 pandemic.

Demand for EV charging

The power demand for EV charging at any hour is a result of the number of charging power, the EV battery size and its SoC. As data on battery size and SoC was not available, the demand for charging had to be estimated based on assumptions. [4] assumed that the cars arrived at the parking lot with SoC uniformly distributed between 20% and 50% and battery capacity in the range 20-80 kWh. [5] used a uniform distribution with the assumption that 70% of the cars arrived at the parking lot with SoC in the range 0-30%, while 30% arrived with SoC in the range 30-80%. [6] on the other hand, assumed cars arrived at the parking lot with an energy demand normally distributed around 50% SoC. We assume an average SoC on arrival at 50 % and a normal distribution. Energy demand on arrival is the gross energy demand to charge the battery to 100% and thus also include losses in the charging process.

Scenarios

Fourteen different scenarios were analysed, and every scenario is simulated one thousand times to evaluate sensitivity. The total number of vehicles parked any hour follow the actual data provided in the dataset. The share of EVs parked is simulated at 25 %, 50 % and 100 %. Moreover, the number of chargers in the scenarios are 250, 500 or 1600 where all parking spots have charger. Two charging power levels are simulated at 3.7 kW and 11 kW respectively. Most of the scenarios are simulated with a normal distribution of charging demand. In scenario 6 is SoC uniformly distributed between 20 % and 60 %, see *Table 1*.

Table 1 Overview of scenarios simulated.

Scenario-number	Number of chargers	Fraction of EVs	Charging power	EV energy demand and standard div	Distribution
1	250	100 %	11	40, 10	Normal
2	250	100 %	3,68	40, 10	Normal
3	250	50 %	11	40, 10	Normal
4	250	50 %	3,68	40, 10	Normal
5	250	50 %	11	60, 5	Normal
6	250	50 %	11	40, 11,55	Uniform [20,60]
7	250	25 %	11	40, 10	Normal
8	250	25 %	3,68	40, 10	Normal
9	500	50 %	11	40, 10	Normal
10	500	50 %	3,68	40, 10	Normal
11	500	100 %	11	40, 10	Normal
12	500	100 %	3,68	40, 10	Normal
13	1600	100 %	11	40, 10	Normal
14	1600	100 %	3,68	40, 10	Normal

Simulation model description

Power demand is calculated for every time step. It is the sum of the electricity for heating and service plus charging.

In step 2, the cumulative energy use from all EVs per month and heating and service are known from step 1. The theoretical minimum charging power that can meet the demand is the average power demand per month. From step 1 the monthly average power demand for each month *m* is calculated. This value provides a constraint on the maximum power available for heating and service plus charging in step 2 if equation 1 is satisfied.

Reference to the paper should be written as: Martinsen, T., G. Devik and H.S. Nygård 2023, Load scheduling and V2G to minimize power demand – exploring potential for airport parking facility, Norway.

The hourly energy demand for heating and service is not flexible and the power demand cannot be lower than the maximum value for heating and service within a month, see equation 1,

$$P_{tot,t} = \begin{cases} P_{avg,m} & if\ P_{avg,m} \geq max\{P_{b,t,}: t = 1..n\}; \\ max\{P_{b,t}: t = 1..n\}, & otherwise \end{cases} \quad (1)$$

where $P_{avg,m}$ is the average power demand per month, $P_{b,t}$ is the power for heating and service per timestep, n is the number of timestep per month and $P_{tot,t}$ is the available power to meet the power demand per timestep.

In step 2 where $P_{tot,t}$ is used, the EVs are queued and the EVs that are leaving first get power first. Step 2 tests if all EVs are fully charged with this approach. If EVs are leaving without being fully charged, $P_{tot,t}$ is increased be one percent until this is true. A vehicle that was parked for shorter duration than the minimum required time to be fully charged was omitted when evaluating an increase in the average power demand.

RESULTS

All scenarios exhibit substantial reduction in the monthly average power demand. Moreover, only slight increase in the average power, 1 – 3 % is required to assure all EVs are fully charged, see *Table 2*.

Table 2 overview of simulation results showing percentage of EVs fully charged by increasing monthly average power by one percentage increments.

Scenario	1	1,01	1,02	1,03
1	92,7 %	100,0 %	100,0 %	100,0 %
2	23,3 %	100,0 %	100,0 %	100,0 %
3	84,9 %	100,0 %	100,0 %	100,0 %
4	73,9 %	100,0 %	100,0 %	100,0 %
5	93,9 %	100,0 %	100,0 %	100,0 %
6	82,7 %	100,0 %	100,0 %	100,0 %
7	100 %	100 %	100 %	100 %
8	98,4 %	100,0 %	100,0 %	100,0 %
9	94,3 %	99,7 %	99,9 %	100,0 %
10	88,7 %	98,9 %	100,0 %	100,0 %
11	99,8 %	100,0 %	100,0 %	100,0 %
12				
13	100,0 %	100,0 %	100,0 %	100,0 %
14	100 %	100 %	100 %	100 %

Overall, the demand for charging with scheduling may be satisfied with only a minor raise in the average power demand. Important for the result is likely the average parking time at 8,7 days. This is most likely because of the long average parking time.

The electricity use for heating and service varies between the seasons and is less than 20 % of the monthly electricity use. However, the diurnal variation is small and the contribution to peak load is negligible. A limited number of hours is causing the high peak power demand and thus a high power cost, see *Figure 3*.

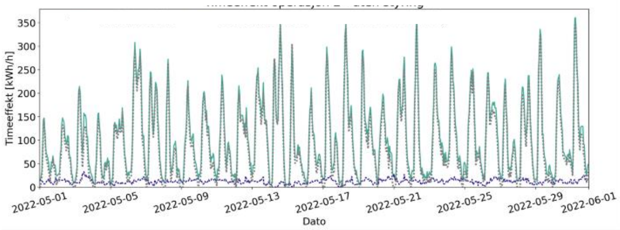

Figure 3 Power demand for charging (green line), and power demand for heating and service during month of May 2022.

Scenarios 9 and 10 exhibit the largest increase in monthly average power demand. The calculated reduction in monthly average power demand is 74 % and 63 % respectively for scenario 9 and 10, see *Figure 4*. However, the power charge is less with the low charging power by 19 % to 43 % depending on the scenario.

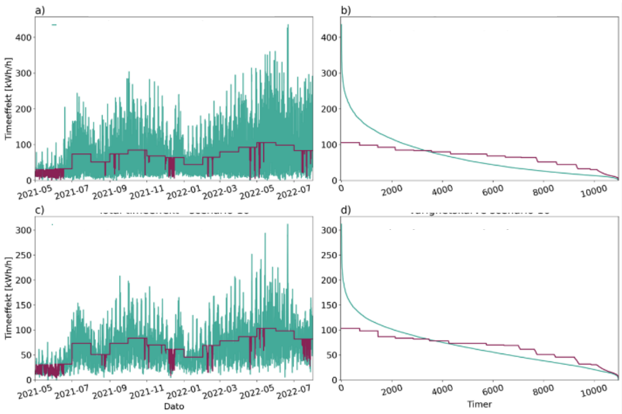

Figure 4 Hourly power demand with (purple line) and without scheduling (green) for scenario 9 (a) and 10 (c). The corresponding load duration curves are given in (b) and (d). Note that the scale in (a) and (b) is 400 kWh/h and in (c) and (d) is 300 kWh/h.

While the power charge may be lower during the summer months, the peak-to-average power is larger. Thus, there is still ample benefit from reducing peak power demand. The high charging power cause a majority of the peaks to become higher and narrower compared to the low charging power.

There are a few time periods when the full capacity of power below the average is not utilized, see *Figure 5*.

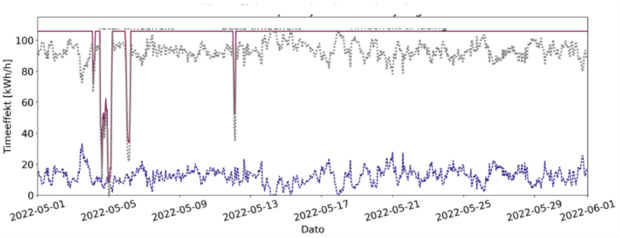

Figure 5 Power demand for the month May showing a few periods where there is available power below the average (purple line). The power for heating and service (blue line) and power for charging (green line).

This is because all EVs are fully charged. While this capacity could have been used to charge and store electricity for later and subsequently use vehicle to grid (V2G) there is no battery capacity to store the energy.

Without scheduled charging the peak power demand coincided with the typical peak power demand in the distribution grid. The spot price generally follows the demand with higher prices at peak demand. Smoothing the power demand through valley filling did, however, hardly reduce the energy cost.

DISCUSSION

Scheduling the EV charging with the constraint to minimize the monthly average power load exhibited a profound potential. Increasing the amount of short-term parking, and thus reducing the average parking time may increase the monthly average power demand. However, we still expect the benefit to be substantial.

Comparing scenario 3, 5 and 6 where the latter has a uniform distribution of charging demand, we find that in more of 800 of the 1000 simulations all EVs where fully charged without increasing the power demand. This indicates that results are not sensitive to the distribution of charging demand upon arrival. Moreover, the assumed charging demand upon arrival is basis for both the reference and the scenarios. A constant error will therefore not influence the results.

During the month of July where almost all the parking spaces where occupied, not all EVs got connected to a charger in scenario 9. We believe this reflects a realistic situation where not every EV parked will demand charging.

In scenario 13 and 14 with 100 % EV-share and all parking spots have charger, all vehicles were fully charged with monthly average power demand in all simulations. As expected, this indicates that with more EVs and chargers the demand exhibits increasing flexibility. In this case it is potential for GP to have a load curve that did not level its own energy use, but rather contribute to level the load curve in the distribution grid. This will be possible with load shifting in combination with V2G. The energy demand by the EVs is still the same, which means that there would be increasing power demand in later hours to compensate. This means higher hourly power demand and thus higher power charges for car park owner. In order to be an attractive average alternative for players with flexible load, the financial incentive for this type of load response must be greater than the incentive from the DSO for a smooth power draw.

CONCLUSION

The results indicate there is large potential to obtain a flat power load curve for the parking facility Gardermoen Parkering. Moreover, only a slight increase in the monthly average power demand is needed to assure all EVs are fully charged upon departure. Compared to uncontrolled charging, the power demand cost was reduced by 61 to 79 % for the various scenarios. The power cost was less with low charging power at 3.7 kW compared 11 kW, but there was a greater percentage saving with a 11 kW charging power as the power peaks where higher initially. The long average parking period facilitated scheduling and introducing V2G would most likely have increasing cost.

Acknowledgments

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