A BUSINESS MODEL FOR AN EV CHARGING STATION WITH BATTERY ENERGY STORAGE

Thomas MARTINSEN
University of Tromsø, Campus Narvik, and
University of Life Sciences – Norway
thomas.martinsen@nmbu.no

ABSTRACT

High power ultra-fast charging stations are required to sustain massive diffusion of electric vehicles. We propose a business model for a charging station with a stationary Li-ion battery pack to alleviate both the high cost of power charges and grid investment. The model accounts for both the energy storage system cost and capacity fade of the batteries. Moreover, we suggest routines for optimizing the economic performance.

NOMECLATURE

p = demand for power
p_{em} = hourly mean power demand without battery
p_e = hourly mean power demand with battery
t = time
T = time of a cycle, e.g., diurnal, monthly or lifetime of battery (months)
CF = capacity fade of the battery
cd = cycle depth
nc = count of cycles (number)
u = temperature in degrees Kelvin
v = temperature in degrees Celsius
k = power tariff
Ce = Power charge
r = interest rate
P_i = The highest hourly grid power demand in month i
η = system efficiency of the charging station
P_a = auxiliary power demand

INTRODUCTION

Fast charging stations for electric vehicles (EV) with a peak power demand of several hundred kW face high operating cost because of power charges in some countries. With a complete shift in the vehicle fleet to EV, demand for fast charging will increase dramatically. Charging of EVs is today predominantly at end-station parking, e.g., home and office. [1] Indicate, based on national statistics for Germany and the UK, that less than 30 % of EV owners in metropolitan areas will have access to home charging. Massive diffusion of fast charging stations will increase peak load and may inflate power tariffs. Typically, energy cost include a small fixed monthly fee, an energy tariff, a power tariff and taxes. In a study of a potential EV fast charging station in Australia [1] found power demand charges to constitute above 90 % of total cost. The reason for this high share is that the demand for fast charging is likely to exhibit a high peak load and a peak power tariff between 5 and 30 US $/month (Wishart, J. 2012 in [2]). The high power cost may be alleviated by a stationary energy storage system (ESS) that smooths the grid power demand. Including ESS at the charging station will in addition to reduced power charges, reduce grid strain and benefit from low energy prices at off peak hours. However, a business model must balance the reduced power charges against the high investment cost of a Li-ion battery ESS.

Power tariffs vary both between countries and within each country depending on the local demand profile and grid capacity. Norway, with a high share of electrical heating have high peak power charge during winter months while Denmark where heating is mostly provided by district heating plants have power tariff only following energy consumption. Sweden, with a combination of electric and district heating have a flat power tariff throughout the year, see Figure 1. Fast charging stations may in the short-term cause power shortage, affecting both the grid and charging availability. With increasing share of intermittent renewable energy generation, new tariffs with economic benefits for energy storage and active participation in the smart energy system is likely to occur.

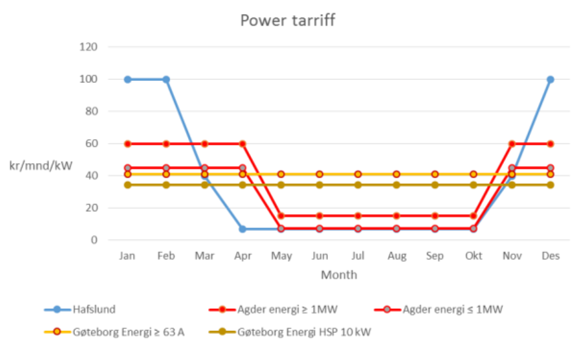

Figure 1 Power tariffs for the Oslo area (blue), a county on the Norwegian south coast (red) and city area of Gotenburg, Sweden.

Megawatt-hour battery containers are being introduced in the European energy system, e.g., at wind farms. Swierczynski [3] notes that the lifetime of the Li-ion battery energy storage is one of the crucial parameters for a business model for a wind power plant with storage. This is equally true for an EV charging station with Li-ion ESS. The battery lifetime is determined upon the capacity fade, often set to 20 – 30 %. The Li-Ion battery capacity fade is highly dependent on several factors, e.g., cycle depth and state of charge during resting time (calendar aging). Li-ion batteries are, together with power charges the most important cost item for the charging station. Thus, minimizing capacity fade and maximizing its lifetime is key to economic sustainability. A dynamic representation of battery capacity fade and lifetime is therefore required.

The various cycles of the model are explained in more detail below, followed by a short discussion and conclusion.

STRUCTURE AND OPERATION OF THE CHARGING STATION MODEL

The model is set up to include all significant cost components affected by the ESS. The investment cost in grid station includes AC/DC conversion, and the battery cost includes DC/DC conversion, battery management control and a system to maintain battery temperature constant, see Figure 2. Operation cost are power and energy charges.

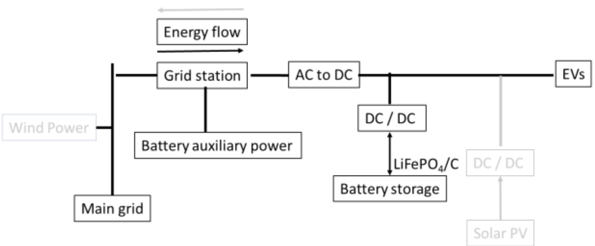

Figure 2 Sketch of the charging station system. The light grey items are options included in the model but not in operation.

Operation principple

The techno-economic model must satisfy an exogenous demand for fast charging. Moreover, grid power capacity may be constrained, e.g., at peak hours. The model consists of three cycles at the time scales diurnal, monthly and economic lifetime of the ESS respectively. The ESS charging and discharging follow a diurnal timescale. In this first cycle we estimate the minimum power demand transferred to the grid and the corresponding charge and discharge of the ESS that minimize the capacity fade. The ESS capacity fade calculations follow each month of operation. In the third cycle, we estimate the economic lifetime of the ESS and the economic performance evaluated. Finally, the optimal size of the ESS is investigated using a neighbourhood search.

Demand for fast charging

The future demand for fast charging is uncertain, but will likely be low or zero during the night and exhibit a peak during the day. In order to test and check the model calculations, I created a diurnal demand profile, see Figure 3. The charging demand profile is not based on real data from charging stations, but includes two peaks of distinctive different magnitude likely to occur.

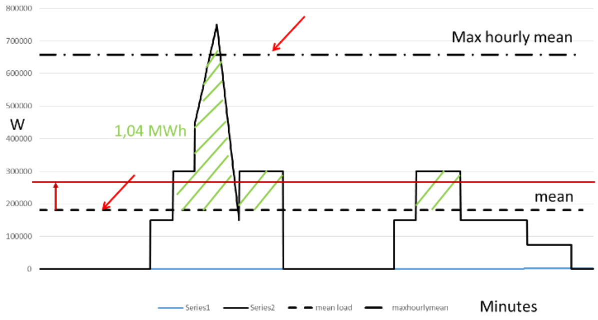

Figure 3 Stylistic EV charging power demand used for model testing. The broken lines are the mean power demand and the maximum hourly mean power demand respectively. The solid line illustrates how the grid power demand increases when battery capacity no longer can provide the energy above mean power level.

Grid power demand

The stationary battery will modify the power demand transferred to the grid. The minimum grid power demand is the average power demand for charging plus auxiliary power and charging station system loss. If the battery energy and power capacity is sufficient to provide all demand for charging above the mean value (striped area in Figure 3), the mean will determine the power charge. The batteries may not have capacity to provide all demand above the average. In order to minimize the peak power demand transferred to the grid the battery capacity is compared with the demand within the following 24-hour period starting from 00h00. Potential battery capacity is determined by state of charge (SOC) at 00h00and charging capacity available. If insufficient the model calculates a new level called "minlevel" that is minimum power demand transferred to the grid for a diurnal period from 00h00 to 24h00, assuming that the ESS is charged when EV charging power demand is below minlevel and discharged when above. Given that the demand for charging is a continuous function F(t) and minlevel is a constant p. I define a function H(t) = 1 for all F(t) - p ≥ 0 and H(t) = 0 for all F(t) - p < 0. The energy demand above p for the first diurnal period is:

Equation 1

$$\int_0^T [F(t) - p] * [H(F(t) - p]dt = L$$

The maximum energy available from the ESS for the first diurnal period is:

Equation 2

$$\int_0^T [p - F(t)] * [1 - H(F(t) - p)]dt \ + SOC(0) = M$$

when the excess power p - F(t) is assumed to charge the battery. SOC(0) is battery stage of charge at the start of the diurnal period and T is the number of timesteps within a diurnal period. Solving L + M = 0 gives the minimum value of p for the charging capacity and given diurnal demand profile. The value of p is further constrained by the charging rate (C-rate) and the maximum battery energy capacity. Currently 0.25 C is set as maximum charging power and 2 C maximum discharging power. Repeating the calculation for 30 days is the second cycle. The highest monthly value of p determines the grid power demand

Equation 3 $P_i = p/\eta + P_a$

Where P_i is the highest hourly average power demand of month i, η is a system efficiency factor less than 1 and P_a is the ancillary power demand.

ESS operation

Minimum capacity fade of a li-ion battery is obtained by cycling and storing the battery around 25 – 50 % of SOC. Thus, we do not want to charge to a higher SOC than is required to meet expected demand for the remaining of the diurnal period. Using equation Equation 2 we find the total potential. Now I rather want to calculate the minimum amount of charging required. At each time-step, the model compares battery SOC with the energy demand above the value of p. If SOC < L' or SOC < SOC(25 %) then the ESS will be charged. L' is the total demand above p for the remaining of the diurnal period.

Battery capacity fade

A Li-ion battery will experience capacity fade from both cycling and storage. While the deterioration differs between cycling and storage, both are sensitive to temperature and, to less extent the average SOC. The average SOC are not included in my equation. Temperature in the ESS is assumed constant, as there is a heating and cooling system. Battery cycles at various depth of discharge (DoD) are counted using a rainflow method and battery resting-time at different SOC is calculated for one month. I assume that the ESS is a $LiFePO_4$/C battery and calculate capacity fade is using a multi-parameter model. According to [4] the capacity fade from cycle aging and calendar aging is respectively:

Equation 4

$$CF_{cycle} = 0.00024 \cdot e^{0.02717\,u} \cdot 0.02982 \cdot cd^{0.4904} \cdot nc^{0.5}$$

Equation 5 $CF_{calendar}=$

$$(0.019 \cdot SOC^{0.823} + 0.5195) \cdot (3.258 \cdot 10^{-9} \cdot v^{5.087} + 0.295) \cdot t^{0.8}$$

After each month, the battery capacity fade is calculated and the corresponding new capacity is basis for the diurnal operation of the model the following month.

ESS lifetime

Because the battery deteriorates, the energy and power capacity of the battery decreases. When/if the battery cannot supply the energy above the mean power demand for charging the power from the grid must increase. Thus, the value of p must increase each month to compensate for the battery capacity fade, see Figure 4. Increasing p increases the power charge while extending the battery lifetime delays reinvestment and thus reduce cost. For this stationary application of ESS, lifetime is identical with economic lifetime. In this calculation, I assume that the reduced electricity cost because charging the ESS mostly is at night is negligible, as well as the cost of auxiliary power. The balance between the reduced power cost and the battery investment thus determines the ESS lifetime.

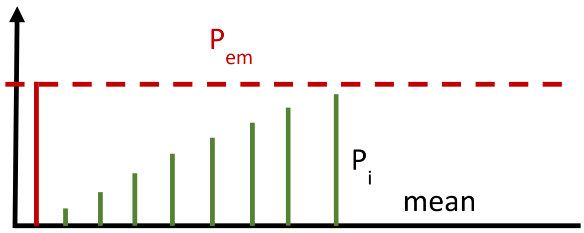

Figure 4 Stylistic illustration of the grid power demand without battery (broken line) and the increasing power demand as battery capacity fades (solid vertical lines).

The reduced power cost is the difference between maximum hourly power demand without battery (p_{em}) and with battery (p_i) multiplied by the power tariff. Moreover, I assume that p_{em} is constant over time. The reduced power cost C_e in month *i* is:

Equation 6 $C_{ei} = k\,(P_{em} - P_i)$

Treating C_{ei} as a continuous function of time Equation 6 may be written as k • f(t). The (re)investment cost for the battery pack C_b is assumed constant. The end of life (EoL) for the battery is thus when the derivative of the discounted sum of the power cost and battery cost is zero.

Equation 7

$$\frac{d}{dT}\langle\langle\int_0^T k \bullet f(t)\, e^{-rt} - Cb\, dt\rangle \, \langle 1 - e^{-rT}\rangle^{-1}\rangle = 0$$

The discount factor $1/(1+r)^t$ is replaced by the continuous time approximation factor $e^{-r\,t}$.

Economic evaluation

The final cycle of the program is a calculation of the net present value (NPV) of the ESS and levelized cost (LCOE) of EV charging. Moreover, the model will search for optimal capacity of the grid connection and the battery.

In the NPV calculation the sum of the reduced power cost, reduced investment in grid station capacity and lower electricity cost are weighed against the additional investment in the ESS including DC/DC converter and cost of auxiliary power demand.

The optimization routine will search in the neighbourhood of the initial battery capacity and grid connection. The investment cost for a grid station is not a continuous function but rather in large discrete steps. Moreover, the grid station capacity must be sufficient to satisfy the demand at the battery EoL.

Result and discussion

Operation of the model with the stylistic demand for charging input shows promising results. Starting with 50 % SOC in the ESS it is charged during the night to 100 % SOC. The discharge follows the peak demand for power. During mid-day the charging of the ESS stops at about 25 % SOC because the small afternoon peak in the stylistic demand profile is barely above the minimum grid power demand (p), see Figure 5. The calculation of this first cycle is repeated for 30 days. The second monthly cycle exhibits increasing values of demand from the grid.

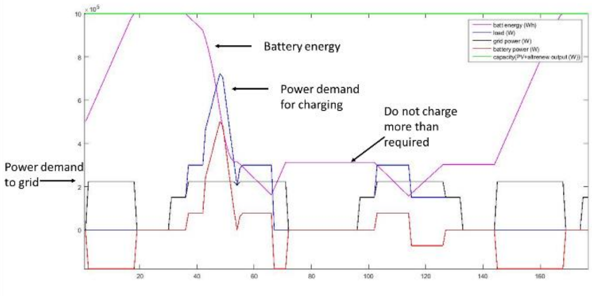

Figure 5 Output from the model for 48 hours showing the battery SOC, charging power demand, power out of the battery and grid power demand.

The development of the this model started from the Energy System Model [5]. The changes required to the model to replace the diesel generator with a grid connection and introducing the Li-ion battery technology have proved substantial. They found that increasing the time resolution from one hour to one minute to account for short-term variation influenced cost, and more significant the capacity of the diesel generator, solar PV and lead acid/Aqueous Hybrid Ion batteries. Their conclusion regarding the time resolution is therefore not directly relevant. However, the need to capture all parameters in sufficient detail is the same. The time resolution of the diurnal calculation may be as low as one minute but currently ten-minute resolution is used. This is about a third of the typical time to charge an EV battery up to 80 % SOC. variations occurring because of connecting and disconnecting EVs at the charging station should thus be captured. Updating the battery capacity at a monthly resolution is sufficient because expected average capacity fade is less than 0.5 % /year. In a business situation, the cycling of the battery may be determined by real-time data.

Other questions prone to be analysed are e.g., minimum total cost or LCOE for charging. Moreover, not using the battery during periods with low power tariff because the power tariff in some grids varies through the year. The investment in the grid station will then be higher and the battery will still lose capacity because of the calendar effect. However, if the grid is sufficient the grid station investment cost is only a tenth of the current battery cost. Such a configuration may also facilitate smart system behaviour charging the ESS when abundant energy is available and supporting the local demand when energy generation is low.

ACKNOWLEDGEMENT

The work is a part of the Flex-ChEV project funded by EU’s Smart Grid ERA-Net program under grant No. 13.

1. Schroeder, A. and T. Traber, *The economics of fast charging infrastructure for electric vehicles.* Energy Policy, 2012. **43**(0): p. 136-144.
2. McPhail, D., *Evaluation of ground energy storage assisted electric vehicle DC fast charger for demand charge reduction and providing demand response.* Renewable Energy, 2014. **67**(0): p. 103-108.
3. Swierczynski, M., *Lithium ion battery energy storage system for augmented wind power plants*, in *Department of Energy Technology*. 2012, Ålborg University: Denmark. p. 144.
4. Swierczynski, M., et al., *Lifetime Estimation of the Nanophosphate LiFePO4/C Battery Chemistry Used in Fully Electric Vehicles.* Ieee Transactions on Industry Applications, 2015. **51**(4): p. 3453-3461.
5. Hittinger, E., et al., *Evaluating the value of batteries in microgrid electricity systems using an improved Energy Systems Model.* Energy Conversion and Management, 2015. **89**(0): p. 458-472.