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Marjan Gjelaj[1]✉ , Nataly Bañol Arias[2], Chresten Træholt[1], Seyedmostafa Hashemi[1]
[1]*CEE-Department of Electrical Engineering, Technical University of Denmark, 2800 Kgs. Lyngby, Denmark*
[2]*Department of Electrical Engineering, UNESP – Sao Paulo State University, Ilha Solteira, São Paulo, Brasil*
✉ *E-mail: margje@elektro.dtu.dk*

Abstract

This paper presents a methodology to improve the operation of the power system and to deal with technical issues caused by electric vehicles (EVs) fast charging load. Fast charging stations (FCSs) are indispensable for widespread use of EVs since they can fully charge EVs in a short period of time. The integration of battery energy storage (BES) within the FCSs is considered a smart option to avoid the power congestion during the peak hours as well as the grid reinforcement costs due to FCSs. In addition, the BES can be used as multifunctional equipment, which is able to provide services such as peak shaving and frequency regulation. This paper proposes a method to determine an optimal size of BES considering a stochastic modelling approach of the EVs load demand based on the users' behaviour and their probabilistic driving patterns. Finally, a case study is carried out using a real DC fast-charging infrastructure in Copenhagen.

Keywords: Electric vehicle, battery energy storage, fast charging station, frequency regulation, peak shaving.

1 Introduction

In recent years, the large-scale electrification of the transport sector has become a major field of research. Fast charging stations (FCSs) become a good option to support the integration of numerous electric vehicles (EVs) in sustainable cities [1], especially when long-distance travel is considered [2]. In the major European cities it has been difficult to install FCSs because its progress poses demanding requirements in terms of EVs battery and charging rate restrictions. In addition, there are many issues related to the impact of the FCSs on the low voltage (LV) distribution network, e.g., congestion during the peak hours, high losses in the feeders [3] and oversizing of electrical equipment [4]. Therefore, FCSs need smart management systems able to predict the required demand and the automotive engineers have proposed their standards on the charging modes [5]. Considering the EV market penetration over the next 10 years [6] the integration of public direct current DC-FCSs are essential to support the future EVs demand and to recharge rapidly in urban areas. Hence, the widespread use of EVs and the installation of the DCFCSs require further research to evaluate their impact on the distribution network and the installation costs for these flexible loads. This topic has been addressed in different literatures. In [7], a coordinated charging system is proposed to minimize the power and maximize the main grid load force to approach an optimal charging profile for EVs. To mitigate the congestion caused by the EV demand, other studies have proposed dynamic price for the users to maintain integrity the electrical grid [8]. Other authors [9] have focused their studies on energy management systems in order to determine an optimal EVs day-ahead scheduling in line with the electricity price. EVs load demand-prediction based on the users' behaviour can help to determine the power required by minimizing the operation costs. Furthermore, EV charging infrastructures play important roles within the smart grids, especially with the spread of different kinds of renewable energy and stationary storage sources [10], [11]. Battery energy storage (BES) can be operated within DCFCSs as multifunctional equipment which is able to provide several services such as peak shaving and frequency regulation [12]–[14]. Additionally, a very important aspect to take into account is the evolution of Li-ion technology and its annual cost reduction [15]. This represents a chance to evaluate possible scenarios of massive EV penetration and to develop control

methods of DCFCSs in order to optimize the operation costs [6]. Assuming the state-of-the-art of the public DCFCSs, this work proposes a methodology for the joint operation of BES and DCFCSs considering the users' driving behaviour. The primary objective is to minimize the EV peak-load demand by avoiding grid reinforcement costs as well as the installation costs of the DCFCs. The secondary objective is to optimize the investment costs of BES by providing frequency regulation during the night when the EV demand can be assumed equal to zero. The main contributions of this paper are: 1) A method to determine the expected charging demand from the DCFCSs according to different properties and probabilistic driving patterns; 2) A stochastic planning method to analyse the EV demand with a coordinated strategy to avoid the peak of the DCFCS load in order to minimize the installation costs by using BES and 3) A strategy to provide frequency regulation services to the transmission system in an attempt to decrease the investment costs of the BES, making DCFCSs with BES a cost-effective solution. The performance of the proposed methodology will be verified and analysed via simulations on a realistic case of DCFCSs in Nordhavn-Copenhagen [1]. The paper is organized as follows. The stochastic model of the public EV FCSs based on the probability distribution functions for the travel distance, state of charge, charging start time and duration of the charging process is described in Section 2. Section 3 presents the operation of the BES within the DCFCs and describes the provision of peak shaving and frequency regulation. The study case and results are presented in Section 4 followed by the conclusions in Section 5.

2 Stochastic Model of the Public DCFCSs

The charging demand of an EV is calculated by the internal battery SoC, charging characteristics and the arrival charging time. The EV battery SoC depends on the travel usage and may be considered as a random variable related to the travel distance. According to the Danish National Transport Survey (DNTS) the average travel distance in Denmark per day is 40.1km with three trips per day [16]. The probability distribution of daily travel distance is calculated as shown in Fig. 1. The distribution of the travel distance is in general expressed as lognormal type *ln* [2] based on the probabilistic distribution function (PDF) and can be expressed as:

$$f(d) = \begin{cases} f(x, \mu_x, \sigma_x) = \dfrac{1}{\sigma_x \sqrt{2\pi}} e^{\frac{-(x-\mu_x)^2}{2\sigma_x^2}} & , x \subset N(\mu_X, \sigma_X) \\ f(d, \mu_d, \sigma_d) = \dfrac{1}{d\sigma_d \sqrt{2\pi}} e^{\frac{-(\ln d - \mu_d)^2}{2\sigma_d^2}} & , d > 0 \end{cases} \quad (1)$$

μ_d and σ_d are the *ln* mean and the standard deviation of the normal distribution. The travel distance analysed in Denmark and shown in Figure 1 has $\mu = 3.6913$ and $\sigma = 0.9361$.
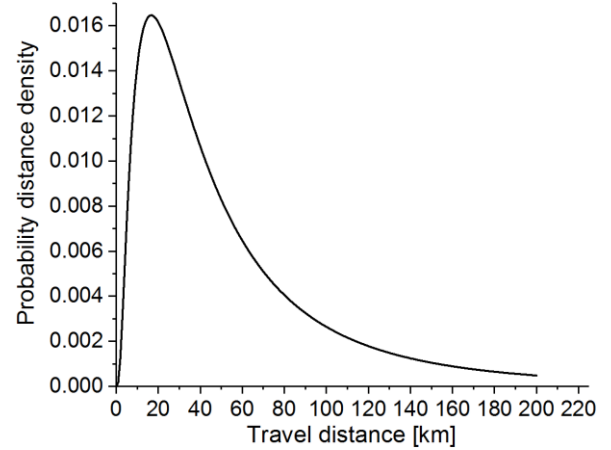

Figure 1: *Denmark: probabilistic distance distribution*

Since the new EVs have a range of 400km or more, the probability distribution of daily travel distance of an EV is assumed the same as a traditional vehicle. Nowadays, the maximum EV range is around 350-450 km with a battery pack of 40, 50 and 60kWh. In this case study the mean is considered 50kWh. The EV energy demand after one-day travel can be calculated using (2), where d is the daily distance driven by a vehicle, η_c is the charger efficiency, V_{ec} is the energy consumption of the vehicle. The current EVs energy consumption may vary from 0,11 kWh/km to 0.2 kWh/km [17].

$$EV_d = (d \cdot V_{ec} \cdot) \cdot \frac{1}{\eta_c} \quad (2)$$

Given the average daily travel distance, the SoC after one day can be calculated as shown in (3).

The SoC_0 is the residual battery capacity after one day of trips, the SoC_1 is dimensionless with value 1.

$$SoC_0 = SoC_1 - \frac{d}{d_{max}}, \qquad 0 < d < d_{max} \quad (3)$$

where d is the daily travel distance by the EV which is a random variable on the lognormal distribution and d_{max} is the maximum range of the EV. Assuming that SoC_0 drops linearly, the travel distance d can be calculated by substituting (3) into (1) and changing variable from d to SoC. The PDF of the SoC after one-day travel distance is obtained as:

$$f(SoC_0, \mu_d, \sigma_d) =$$

$$\frac{1}{(SoC_1 - SoC_0)d_{max}\,\sigma_d \sqrt{2\pi}} e^{\frac{-\left[(\ln(SoC_1 - SoC_0) + \ln(d_{max}) - \mu_d)\right]^2}{2\sigma^2}} \quad (4)$$

The daily vehicle travel distance and the probability SoC density are based on the two stochastic variables calculated in (1), (4). The SoC after a certain number of trips d_n can be calculated as:

$$SoC_n = SoC_1 - \frac{d_n}{d_{max}} \quad (5)$$

where SoC_n is the remaining battery capacity after a number of trips, SoC_1 is dimensionless with value 1. The start charging time depends on the users' driving behaviour, and the charging duration on the charging power rate which, for this case study is 150kW [17]. The charging time depends on the users' behaviour, and different factors need to be analysed, such as the home environment, work environment, and traffic density. For example, in the urban area during the workday, the drivers will prefer to charge their EVs close to home or work [18].

2.1 Probability start charging time

Copenhagen municipality executes an annual report of the traffic flow on predefined roads to validate a car traffic model during workdays and weekends. The probability driving density provided by DNTS considers the travel users' behaviour with traditional cars. Considering EVs with more than 400 km the EV users' behaviour is assumed to be similar. The traffic data were obtained by observing 398 induction spools beneath the road surface with 5 min resolution [18]. The probability driving density can be used to obtain important parameters related to the users' driving behaviour. Fig. 2 shows the daily commutes in Copenhagen (from home to work and vice versa) and the weekend commutes. In Copenhagen, many drivers refuel their vehicles before going to work from 7:00 to 9:00 am or after work from 16:00 to 19:00. The correlation between the probability driving density and the refueling driving behaviours on the temporal distribution probability has been demonstrated in [19]. Then, the charging start time of the DCFCSs in mode 4 [5],[17] will follow the probability refueling driving behaviour on the temporal distribution as shown in (6) [19].
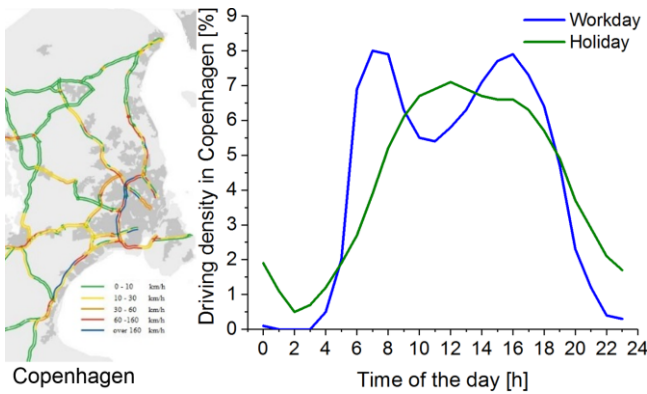

Figure 2: *Probability driving density in Copenhagen [18]*

$$f(t_{st}, \mu_{st}, \sigma_{st}) = \frac{1}{\sigma_{st}\sqrt{2\pi}} e^{\frac{-(t_{st}-\mu_{st})^2}{2\sigma_{st}^2}} \quad , \qquad 0 < t_{st} < 23 \quad (6)$$

t_{st} is the starting charging time of the FCSs, μ_{st} and σ_{st} are the mean and the standard deviation of the starting charging time. μ_{st} and σ_{st} are based on the arrival time probability distribution calculated on the current refuelling driving behaviour in [19].

2.2 Probability charging duration

The charging duration t_{cd} is based on the equations (1),(4) and its corresponding PDF can be calculated in (7) as:

$$f(t_{cd}, \mu_d, \sigma_d) =$$

$$\frac{\eta_c P_{dc}}{(SoC_1 - SoC_n)\sigma_d\sqrt{2\pi}} e^{\frac{-(\ln(\frac{(SoC_1-SoC_n)C_{max}}{\eta P_{dc}})-\mu_d)^2}{2\sigma_d^2}} \quad (7)$$

the SoC when arriving and leaving the DCFCS is represented by (6) and (7), η_c is the charger efficiency, P_{dc} is the nominal power of the DCFCS and C_{max} represents the maximum capacity of the EVs battery. P_{dc} in the case study is 150kW with 90% of efficiency.

2.3 Probability of EVs daily demand

After defining the probabilistic models described in (6) and (7), the corresponding daily charging demand of multiple EVs at instant t can be calculated by (8) and (9) as:

$$p_N = p(p_{st} \cap p_{cd}) = p_{st} \cdot p_{cd} \quad (8)$$

$$P_{tcl}(t) = \begin{cases} P_{cl}(t) = p_N \cdot N(t) \cdot P_{dc}(t) \cdot \eta_c \\ P_{tcl}(t) = \sum_{i=1}^{N_i} p_{N_i} \cdot N_i(t) \cdot P_{dc,i}(t) \cdot \eta_c \end{cases} \quad (9)$$

Where p_N represents the intersection probability of two independent variables, the PDFs of the start charging time and the charging duration of the DCFCSs calculated in (6) and (7), respectively. p_{st} and p_{cd} are the probabilities of the $f(t_{st})$ and $f(t_{cd})$ at the time t_{st} and t_{cd}. P_{cl} is the charging load at time t, N is the number of EVs under consideration at the time t. P_{dc} is the power of the DCFCSs based on the number of the charging spots and their efficiency. $P_{tcl}(t)$ is the total charging load consumed during the day.

2.4 DCFCS configuration based on the EVs daily demand

In this section, the proposed stochastic planning method is presented in order to evaluate the EV public charging stations and their grid impact.

For this purpose, it is defined that the EVs demand must satisfy the grid conditions:

$$P_g(t) \leq P_{bl}(t) + \sum_{i=1}^{N_i} p_{N_i} \cdot N_i(t) \cdot P_{dc,i}(t) \cdot \eta_c \qquad (10)$$

$P_{bl}(t)$ is the base load at the interval t (i.e., the total load excluding the charging load in the feeder) and $P_g(t)$ is the required grid power to support the EVs demand. Considering (5) after a certain number of trips, the maximum EVs daily demand EV_d can be calculated as follows:

$$EV_d = \begin{cases} SoC_n < SoC_{next\,trip} \quad , \; SoC_n = \dfrac{d-1}{d_{max}} \approx 0.098 \\ EV_d = [N \cdot (SoC_1 - SoC_n) \cdot d_{max} \cdot V_{ec}] \cdot \dfrac{1}{\eta_c} \end{cases} \qquad (11)$$

The vehicle energy consumption V_{ec} of the new EVs model can be considered as 0.15kWh/km with η_c in DC at 90%. Table I shows different EVs daily demand scenarios and the minimum power required from the grid. The network parameters and the number of charging spots can be modelled according to the selected scenario.

Table 1: *Grid power and charging spots based on the EV demand*

EVs daily demand	EV daily demand [kWh]	Grid power [kW]	Number DCFCS 50kW	Number DCFCS 150kW	Number DCFCS 300kW
15	902	73.1	2	1	1
20	1804	146.1	3	1	1
60	3608	292.2	6	2	1
90	5412	438.4	9	3	2
120	7216	584.5	12	4	2
150	9020	730.6	15	5	3

$$P_{grid} = \frac{EV_d}{\Delta_x} \qquad (12)$$

P_{grid} is the minimum required grid power, calculated using a conversion factor Δ_x which represents the maximum EV demand during the congested peak hour [19]. Considering the growing number of EVs more chargers are required and in many cases the total charging load $P_{tcl}(t)$ may exceed the grid power capacity. Therefore, to face this problem there are two solutions: grid reinforcement through the installation of a new transformer or the integration of BES within the DCFCSs as proposed in the next section.

3 Operation of the BES within DCFCS

3.1 Peak shaving via BES

In this section, an optimal peak management is proposed to minimize the EV peak demand during the congestion hours by using BES as stationary application. As a result of the coordinated strategy, reduction of the grid reinforcement costs e.g., new dedicated lines and new transformer's substation are expected. Coordinated storage charging interface design must take into account the system's overall energy balance in specified time:

$$\begin{aligned} E_b(t) &= \sum_{t=1}^{T} \left(E_{b,ch}(t) \cdot \eta_{ch} - \frac{E_{b,dis}(t)}{\eta_{dis}} \right) \\ &= \sum_{t=1}^{T} \left(E_g(t) - E_{bl}(t) - \sum_{i=1}^{N_i} E_{tcl,i}(t) \right) \end{aligned} \qquad (13)$$

$E_g(t)$ is the limited grid energy, $E_b(t)$ is the energy given or absorbed from the BES, η_{dis} and η_{ch} are the BES's converter efficiency during the discharging and charging process. The $E_{b,ch}(t)$ is the BES charging energy and $E_{b,dis}(t)$ is the discharging energy. η_{ch} and η_{dis} are the conversion efficiencies at 90%. The $E_{bl}(t)$ is the base load at the interval t, which is the total load excluding the charging load in a certain feeder and in this case $E_{bl}(t)$ is equal to zero. The BES capacity can be calculated as a function of the EVs daily demand. During the EVs charging demand the BES operates in parallel with the DCFCSs and the peak shaving (PS) will be provided during the congestion hours due to the high EV demand. The BES charging power is limited by the available grid power $P_g(t)$. The discharging power is defined by the converter's rated power and the difference between the grid and EV charging power (14). The objective function is used to minimize the energy peak load demand by using the minimum BESs within the DCFCSs as described in the following equations:

$$\begin{cases} \min \left(\max \left(\sum_{t=1}^{T} (E_b(t)) \right) \right) \\ E_b(t) = E_g(t) - E_{bl}(t) - \sum_{i=1}^{N_i} (p_{N_i} \cdot N_i(t) \cdot (E_{dc,i}(t) \cdot \eta_c)) \\ E_g(t) < E_{bl}(t) + \sum_{i=1}^{N_i} (p_{N_i} \cdot N_i(t) \cdot (E_{dc,i}(t) \cdot \eta_c) - \frac{E_{b,dis}(t)}{\eta_{dis}} \\ E_g(t) > E_{bl}(t) + \sum_{i=1}^{N_i} (p_{N_i} \cdot N_i(t) \cdot (E_{dc,i}(t) \cdot \eta_c) + E_{b,ch}(t) \cdot \eta_{ch} \\ \qquad\qquad \frac{E_{b,dis}(t)}{\eta_{dis}} \leq E_b(t) \end{cases} \qquad (14)$$

3.2 Frequency Regulation via BES

Frequency regulation is a common ancillary service procured by transmission system operators (TSOs) to balance consumption and production in real time while maintaining the system stability. BES are a suitable option for frequency regulation due to their fast response. However, the initial investment costs of the BES are directly proportional to the physical size and capabilities of the storage unit, i.e., the battery and the charger, which results in high capital costs. Considering that frequency regulation is one of the most profitable services [20], a strategy for a BES providing frequency regulation is proposed in an attempt to reduce their capital costs. In Denmark, several frequency regulation services are procured according to two areas termed Western Denmark or (DK1) and Eastern Denmark or (DK2) [21]. The BES subjected to this analysis will provide frequency-controlled normal operation reserve (FNR) to Energinet (the TSO in Denmark). FNR is a service found in Denmark, area DK2, and corresponds to a symmetric frequency control activated for both under and over frequencies. The aim is to automatically stabilize the frequency at 50Hz and minimize frequency deviations following the linear function (i.e droop control) depicted in Fig. 7.
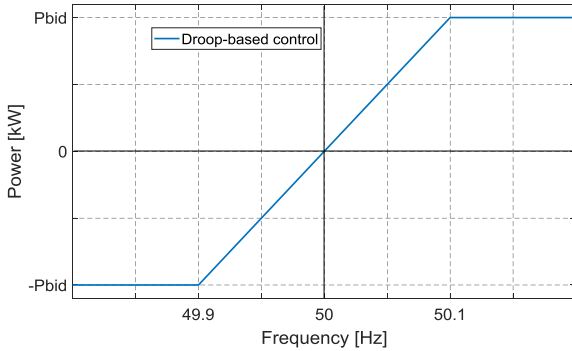

Figure 7: *Droop control for FNR*

According to the Danish market rules the minimum bid must be 0.3MW and should be submitted one or two days ahead of the day of operation containing volume (MVs) and the hour-by-hour price (DKK/MW or EUR/MW). Moreover, the service is compensated based on an availability payment and pay-as-bid [21]. In this context a control strategy is proposed to provide FNR when the BES is not providing other services, i.e., peak shaving. The provision of FNR is proposed in an attempt to decrease the investment costs of the BES (according to the characteristics of the BES defined in the Section 3.1). Considering these characteristics and also the market rules for FNR, the power bid is defined to be 300kW. FNR will be provided during the night when the battery remains mostly idle in order to reduce the risk related to the bidding process. Moreover, specific time intervals will be used to restore the battery SoC to be able to provide peak shaving during the daytime. The BES charging and discharging power when providing FNR is also limited by the available grid power and the converter capacity defined in

(14) and (15). The problem consists on maximizing the profit for providing FNR as described in (15). The objective function is to maximize the power bid $P_{bid}(t)$, which is offered in the day-ahead. Since the profit for this service is calculated based on a capacity payment, it is expected that the more power bid, the greater the profit. In this case $P_b^{FR}(t)$ is a parameter which represents the power required as a function of the frequency deviation from 50Hz and the droop control depicted in Fig. 7. The remaining equations represent the operation of the battery in terms of the power and SoC limitations along the complete regulation period total frequency regulation (TFR).

$$
\begin{cases}
\max \sum_{t=1}^{TFR} P_{bid}(t) \\
\left| P_b^{FR}(t) \right| \le P_{bid}(t) \\
P_{bid}(t) \le P_g \\
\underline{E} \le E_b(t) \le \bar{E} \\
E_b(t) = E_{b,ch}(t) = E_b(t-1) + P_b^{FR}(t) \cdot \Delta(t) \cdot \eta_{ch}, \quad if\ P_b^{FR}(t) > 0 \\
E_b(t) = E_{b,dis}(t) = E_b(t-1) - \dfrac{P_b^{FR}(t) \cdot \Delta(t)}{\eta_{dis}}, \qquad if\ P_b^{FR}(t) < 0
\end{cases}
\tag{15}
$$

3 Simulations and Results

In this section, a simulation-based approach is used to underline the performance of the proposed methodology. For this purpose the following assumptions are considered: a) The DCFCSs and the BES belong to the same private stakeholder, which is also responsible for grid upgrade; b) Peak shaving is a local service provided electric vehicle supply equipment operators (EVSEO), and it will be performed to manage the EV demand during the congestion hours in order to avoid the grid reinforcement costs, and c) Frequency regulation is a service provided for the transmission system, and it will be performed in order to compensate the investment costs of the BES.
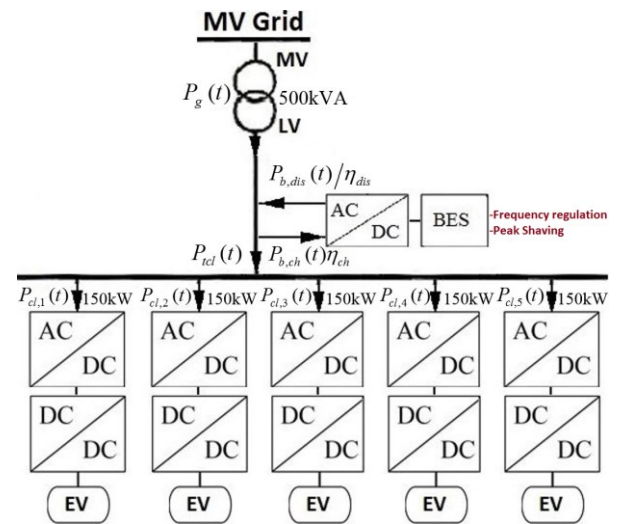

Figure 8: *Grid configuration with 150 EVs per day (Table 1)*

The configuration of the LV distribution grid is depicted in Fig. 8 corresponding to one demand scenario with 150 EVs according to Table 1. As can be seen in Fig. 8, five charging spots are required to support the daily EV demand, which is obtained by using Table 1.

Under this scenario, the battery was sized according to (14) to avoid the peak resulting from the EV charging. Thus, the BES capacity is 437 kWh, and the power capacity of the charger is 300 kW, considering the limitation of the grid, i.e., the transformer capacity. Fig. 9 depicts the BES operation after 1-day simulation.
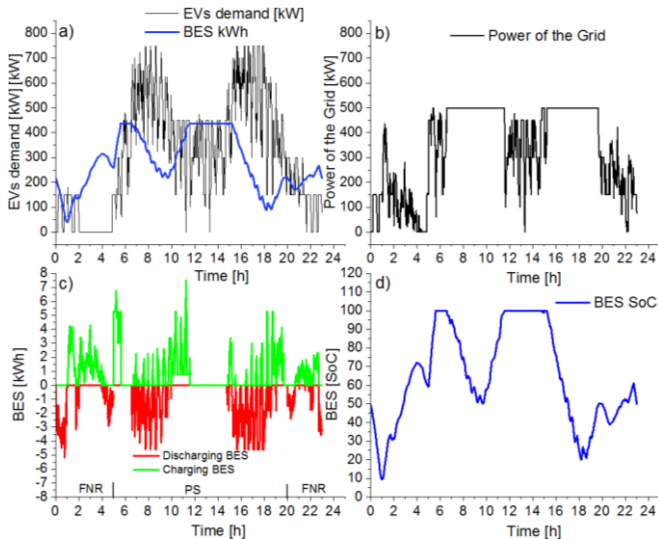

Figure 9: *BES operation after 1-day simulation*

In Fig. 9, charging peaks can be observed early in the morning (between 06:00 and 10:00) and in the afternoon (between 16:00 and 19:00) in accordance with user's behaviour. Note from Fig. 9, that the BES is discharged during those periods supporting the grid via peak shaving. Moreover, the period between 12:00 and 16:00 is used to restore the SoC of the battery and being prepared to provide peak shaving during the second peak of the day. Additionally, as shown in Fig. 9 the BES is providing FNR during the period from 20:00 to 05:00 of the next day. During this period of time, the BES is charged or discharged according to the frequency signal. Similar to the peak shaving application, the periods from 05:00 to 06:00 and from 19:00 to 20:00 are used to restore the battery SoC to be able to provide peak shaving during the daytime.

According to Fig. 9, the introduction of the BES helps the DCFCSs to avoid the grid reinforcement when the EVs peak demand exceeds the grid capacity (9). The equation (14) is implemented in order minimize the grid reinforcement costs of the DCFCSs demand by using an optimal BES. Instead, (14) and (15) are used to maximize the profitability of the BES versus its investment costs by providing peak shaving and frequency regulation. The financial performance of the BES costs versus grid reinforcement costs can be calculated through a cost-benefit analysis as suggested in [22].

4 Conclusion

In this paper a stochastic methodology was presented to determine the daily demand of EVs based on the users' behaviour and their probabilistic driving patterns. The proposed method helps to minimize the DCFCSs grid installation costs by using an optimal BES size within the DCFCSs. The BES size was defined as function of grid constraints and the EVs energy demand based on the EV user's behaviour in order to avoid the grid reinforcement costs. In addition, the BES operation costs are minimized by providing ancillary services as peak shaving and frequency regulation. In this case, the revenues for these services are given by the energy sold to the EV users during the peak hours plus the availability payment for being able to provide FNR during the night. Therefore, the proposed methodology can be used as a smart alternative to avoid additional grid reinforcement costs caused by the EVs peak demand during the peak hours. As future works, a cost-benefit analysis can be carried out to evaluate the financial performance of the BES costs versus grid reinforcement costs, or further methodologies can be proposed to optimize the power bid within the power systems.

Acknowledgements

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