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Multifunctional applications of batteries within fast-charging stations based on EV demand-prediction of the users’ behaviour

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Abstract: This study 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 study 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.

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 DC-FCSs 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 kinds of literature. In [7], a coordinated charging system is proposed to minimise the power and maximise 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 a dynamic price for the users to maintain integrity of the electrical grid [8]. Paterakis et al. [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 minimising 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 DC-FCSs as multifunctional equipment which is able to provide several services such as peak shaving (PS) 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 DC-FCSs in order to optimise the operation costs [6]. Assuming the state-of-the-art of the public DC-FCSs, this work proposes a methodology for the joint operation of BES and DC-FCSs considering the users’ driving behaviour. The primary objective is to minimise the EV peak-load demand by avoiding grid reinforcement costs as well as the installation costs of the DC-FCSs. The secondary objective is to optimise 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 study are: (i) a method to determine the expected charging demand from the DC-FCSs according to different properties and probabilistic driving patterns; (ii) a stochastic planning method to analyse the EV demand with a coordinated strategy to avoid the peak of the DC-FCS load in order to minimise the installation costs by using BES and (iii) a strategy to provide frequency regulation services to the transmission system in an attempt to decrease the investment costs of the BES, making DC-FCSs with BES a cost-effective solution. The performance of the proposed methodology will be verified and analysed via simulations on a realistic case of DC-FCSs in Nordhavn, Copenhagen [1]. The paper is organised as follows. The stochastic model of the public EV FCSs based on the probability distribution functions for the travel distance, state of charge (SoC), charging start time and duration of the charging process is described in Section 2. Section 3 presents the operation of the BES within the DC-FCSs and describes the provision of PS 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 DC-FCSs

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 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 40.1 km 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 in general is expressed as log-normal type ln[2] based on the probabilistic distribution function (PDF) and can be expressed as:
depends on the users’ driving behaviour, and the charging duration calculated using (2), where the daily travel distance driven by a vehicle, \( n_c \) is the charger efficiency, and \( V_{ec} \) is the energy consumption of the vehicle. The current EVs’ energy consumption may vary from 0.11 to 0.2 kWh/km [17]

\[
EV_d = (d \cdot V_{ec}) \cdot \frac{1}{n_c}.
\]

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

\[
SoC_0 = SoC_1 - \frac{d}{d_{max}}, \quad 0 < d < d_{max},
\]

where \( d \) is the daily travel distance by the EV which is a random variable on the log-normal 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 the variable from \( d \) to SoC. The PDF of the SoC after one-day travel distance is obtained as

\[
f(\text{SoC}_n, \mu_c, \sigma_c) = \frac{1}{\sigma_c \sqrt{2\pi}} e^{-\frac{(\text{SoC}_n - \mu_c)^2}{2\sigma_c^2}}, \quad 0 < \text{SoC}_n < 23,
\]

where \( \text{SoC}_n \) 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 150 kW [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 of 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 refuelling driving behaviours on the temporal distribution probability has been demonstrated in [19]. Then, the charging start time of the DC-FCSs in mode 4 [5, 17] will follow the probability refuelling driving behaviour on the temporal distribution as shown in (6) [19]

\[
f(t_0; \mu_{cd}, \sigma_{cd}) = \frac{1}{\sigma_{cd} \sqrt{2\pi}} e^{-\frac{(t_0 - \mu_{cd})^2}{2\sigma_{cd}^2}}, \quad 0 < t_0 < 23,
\]

where \( t_0 \) is the starting charging time of the FCSs, \( \mu_{cd} \) and \( \sigma_{cd} \) are the mean and standard deviation of the starting charging time. \( \mu_{cd} \) and \( \sigma_{cd} \) 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 (1) and (4) and its corresponding PDF can be calculated in (7) as

\[
f(t_{cd}; \mu_{cd}, \sigma_{cd}) = \frac{1}{\sigma_{cd} \sqrt{2\pi}} e^{-\frac{(t_{cd} - \mu_{cd})^2}{2\sigma_{cd}^2}}, \quad 0 < t_{cd} < 23,
\]

where the SoC when arriving and leaving the DC-FCSs is represented by (6) and (7), \( n_c \) is the charger efficiency, \( P_{dc} \) is the nominal power of the DC-FCS and \( C_{max} \) represents the maximum capacity of the EVs battery. \( P_{dc} \) in the case study is 150 kW 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

\[
\begin{align*}
\nu_t & = \nu_t(p_{\nu} \cap p_{\mu}) = p_{\nu} \cdot p_{\mu}, \\
\nu_{dc}(t) & = \sum_{i=1}^{N} p_{\nu} \cdot N(t) \cdot P_{dc}(t) \cdot \eta_c,
\end{align*}
\]

where \( \nu_t \) represents the intersection probability of two independent variables, the PDFs of the start charging time and the charging duration of the DC-FCSs calculated in (6) and (7), respectively. \( P_{dc} \) and \( \nu_{dc}(t) \) are the probabilities of the \( F_{dc}(t) \) and \( \nu_{dc}(t) \) at the time \( t \), and \( t_{dc} \) 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 DC-FCSs based on the number of charging spots and their efficiency. \( \nu_{dc}(t) \) is the total charging load consumed during the day.

2.4 DC-FCS configuration based on the EVs daily demand

In this section, the proposed stochastic planning method is presented in order to evaluate the public charging stations and their grid impact. For this purpose, it is defined that the EVs demand must satisfy the grid conditions:

\[
P_g(t) \leq P_{gb}(t) + \sum_{i=1}^{N} p_{\nu} \cdot N(t) \cdot P_{dc}(t) \cdot \eta_c,
\]

where \( P_{gb}(t) \) 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 \( E_{V_d} \) can be calculated as follows:

\[
EV_d = \begin{cases} 
\text{SoC}_b < \text{SoC}_{\text{max trip}}, & \frac{d - 1}{d_{\text{max}}} \approx 0.098, \\
\text{SoC}_b \geq \text{SoC}_{\text{max trip}}, & EV_d = [N \cdot (\text{SoC}_b - \text{SoC}_a) \cdot d_{\text{max}} \cdot V_{ec}] \cdot \frac{1}{\eta_b}.
\end{cases}
\]

The vehicle energy consumption \( V_{ec} \) of the new EVs model can be considered as 0.15 kWh/km with \( \eta_b \) in DC at 90%. Table 1 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

\[
P_{grid} = \frac{EV_d}{\Delta x}
\]

where \( P_{grid} \) is the minimum required grid power, calculated using a conversion factor \( \Delta x \), 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 \( P_{grid}(t) \) 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 DC-FCSs as proposed in the next section.

3 Operation of the BES within DC-FCS

3.1 PS via BES

In this section, optimal peak management is proposed to minimise the EV peak demand during the congestion hours by using BES as a 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 a specified time

\[
E_d(t) = \sum_{i=1}^{T} \left( E_{b, ch}(t) \cdot \eta_{ch} - E_{b, ch}(t) \right) \eta_{dis}
\]

where \( E_d(t) \) is the limited grid energy, \( E_d(t) \) is the energy given or absorbed from the BES, \( \eta_{dis} \) and \( \eta_{ch} \) are BES's converter efficiency during the discharging and charging process. \( E_{b, ch}(t) \) is the charging energy and \( E_{b, dis}(t) \) is the discharging energy, \( \eta_{ch} \) and \( \eta_{dis} \) are the conversion efficiencies at 90%. The \( E_d(t) \) 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 \( E_d(t) \) 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 DC-FCSs and the 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 minimise the energy peak load demand by using the minimum BESs within the DC-FCSs as described in the following equations:

\[
\begin{align*}
E_d(t) & = E_d(t) - E_{gb}(t) - \sum_{i=1}^{N} (p_{\nu} \cdot N(t) \cdot (E_{b, ch}(t) \cdot \eta_c)), \\
E_d(t) & = E_d(t) + \sum_{i=1}^{N} (p_{\nu} \cdot N(t) \cdot (E_{b, dis}(t) \cdot \eta_c) - E_{b, dis}(t) \eta_{dis}).
\end{align*}
\]

3.2 Frequency regulation via BES

Frequency regulation is a common ancillary service procured by transmission system operators (TSOs) to balance consumption and...
day of operation containing volume 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. PS. 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 Section 3.1). Considering these characteristics and also the market rules for FNR, the power bid is defined to be 300 kW. 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 PS 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 of maximising the profit for providing FNR as described in (15). The objective function is to maximise the power bid \( P_{\text{bid}}(t) \), 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, \( P_{R}^{FNR}(t) \) is a parameter, which represents the power required as a function of the frequency deviation from 50 Hz and the droop control depicted in Fig. 3. 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) (see (15)).

4 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 DC-FCSs and the BES belong to the same private stakeholder, which is also responsible for grid upgrade; (b) PS is a local service provided to electric vehicle supply equipment operators, 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.

The configuration of the LV distribution grid is depicted in Fig. 4 corresponding to one demand scenario with 150 EVs according to Table 1. As can be seen in Fig. 4, 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. 5 depicts the BES operation after 1-day simulation.

In Fig. 5, 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. 5, that the BES is discharged during those periods supporting the grid via PS. Moreover, the period between 12:00 and 16:00 is used to restore the SoC of the battery and being prepared to provide PS during the second peak of the day. Additionally, as shown in Fig. 5 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 with the optimal operation described in (14) and (15).
discharged according to the frequency signal. Similar to the PS 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 PS during the daytime.

According to Fig. 5, the introduction of the BES helps the DC-FCSs to avoid the grid reinforcement when the EVs peak demand exceeds the grid capacity (9). Equation (14) is implemented in order to minimise the grid reinforcement costs of the DC-FCSs demand by using an optimal BES. Instead, (14) and (15) are used to maximise the profitability of the BES versus its investment costs by providing PS 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].

5 Conclusion

In this study, 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 minimise the DC-FCSs grid installation costs by using an optimal BES size within the DC-FCSs. The BES size was defined as a 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 minimised by providing ancillary services as PS 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 optimise the power bid within the power systems.

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